

An Attention-Based Deep Learning Framework for Multi-Class Tourist Satisfaction Analysis

Jyotsana Tewari¹, Sudhanshu Kumar Jha²

¹Department of Electronics and Communication, Faculty of Science, University of Allahabad, Prayagraj – 211002, INDIA.

E-mail: jyotsanatewari1991@gmail.com

²Department of Electronics and Communication, Faculty of Science, University of Allahabad, Prayagraj – 211002, INDIA.

E-mail: skjha@allduniv.ac.in

*Corresponding Author: Sudhanshu Kumar Jha, E-mail: skjha@allduniv.ac.in

Abstract

Customer satisfaction is one of the most important factors influencing service quality, market competitiveness, and long-term growth in the tourism and hospitality sector. As online travel websites and review platforms continue to expand, analyzing customer feedback automatically has become essential for understanding visitor experiences and improving services. However, tourist reviews are generally unstructured, large in volume, and contain high-dimensional textual information, which makes accurate analysis difficult for traditional machine learning methods. To overcome these challenges, this research presents an attention-driven deep learning model for multi-class tourist satisfaction classification. The proposed framework employs dense neural layers to learn meaningful feature representations, along with parallel projection layers and an adaptive attention mechanism that highlights the most relevant review patterns. This design enables the model to capture semantic relationships more effectively and improve sentiment classification across multiple categories. The experimental results indicate that the proposed framework performs consistently well and converges stably during training. The model achieves an overall classification accuracy of 84%, while the macro and weighted F1-scores reach 0.85, showing balanced performance across sentiment classes. In addition, the average Area under the Curve (AUC) value of 0.98 demonstrates strong discriminative capability. Precision-Recall evaluation further validates the reliability of the framework, with average precision values ranging from 0.94 to 0.95. Confusion matrix analysis also confirms that the model can effectively distinguish among different satisfaction levels with minimal severe misclassification. Overall, the study highlights the effectiveness of attention mechanisms in improving feature learning and predictive performance, making the framework suitable for practical tourism analytics and intelligent hospitality management applications.

Keywords: Deep Learning, Attention Mechanism, Sentiment Analysis, Tourist Satisfaction, Hospitality Industry, Multi-class Classification.

1. Introduction

The international tourism sector has been experiencing a fast development of cultural tourism. Cultural attributes are highly relevant for the postmodern society, especially with regard to economic issues, consumer satisfaction is a noteworthy concept within the research of tourism. The tourism industry has been reflecting a rapid growth due to a heightened state of cultural exchange, advancement, and growth of the internet, and augmented utilization of online travel services. In this regard, customer satisfaction has increased in importance as a factor that determines success. Online reviews are currently the major source of vital information on customer perceptions, feelings, and expectations. The sheer amount, lack of structure, and complexity of the lexicon used in this type of analysis result in significant difficulties with the analysis process, making it necessary to resort to deep learning solutions. Although machine learning has been used with success, it is still challenged with a lack of deep learning comprehension in high-dimensional texts. The development of deep learning solutions, especially with attention mechanisms, has proven a significant solution to this problem. This research thus proposes a deep learning solution that is based on the attention mechanism, with a goal of applying a deep learning approach to accurately classify tourist satisfaction with a touristic service into five categories. The major contributions of this study are outlined below:

An attention-oriented deep learning framework is introduced for multi-class tourist satisfaction prediction using high-dimensional review datasets. The proposed model integrates dense feature learning, parallel feature projection, and an adaptive attention strategy to enhance representation learning and improve classification outcomes.

1. The proposed framework is capable of processing sparse and high-dimensional textual information efficiently while controlling overfitting through dropout regularization techniques.

2. A comprehensive experimental evaluation is carried out using several performance measures, including accuracy, F1-score, ROC-AUC, Precision-Recall analysis, and confusion matrix evaluation.

3. The proposed approach achieves an accuracy of 84% with strong generalization performance, demonstrating its suitability for real-world tourism and hospitality analytics systems.

The rest of the paper is drafted as follows: Literature work related to the study of work presented here is described in section 2.

2. Related Work

This, in turn, further increases the integration of machine learning and artificial intelligence into hospitality and tourism industries, regarding the look onto customer behavior, operations management, and raising the quality of services provided. According to Alotaibi (Alotaibi et al., 2020), though the hotel industry is somewhat behind in including ML into its practice compared to other businesses, the potential is huge. This is evident by the fact that the current study is a decade-old review that clearly shows significant contributions of ML to demand and pricing prediction, prediction of cancellation, and efficiency of operations. It is further evident that, according to the same study, major followers of this technology are China and the USA; however, there is a need for expansion of ML implementation in the hospitality industry globally. Different research has been done to analyze sentiment and predict ratings from online reviews, which are the major source of information in the tourism sector. The work of Puh and BagićBabac (Puh and Bagić Babac, 2023) used 20,491 exposed TripAdvisor reviews to perform a comparison between machine learning and deep learning models for sentiment analysis. It turned out that deep learning techniques, especially BiLSTM, outperform traditional models like Naïve Bayes and SVM. The findings indicate an increased importance of the use of complex neural networks for interpreting data from large volumes of online text, supporting tourists' and service providers' decision-making processes. Big social data analysis is also used extensively in measuring the trends of customer satisfaction. In research that targeted hotels in the city of Mecca, Alsayat (Alsayat et al., 2023) proposes a hybrid solution that incorporates supervised learning, topic modeling, and segmentation analysis. In this research, the author applies the use of SVR-SMO, LDA, and k-mean clustering to analyze different types of travelers and how certain posts on the website are an indication of certain satisfaction levels. More granular forms of sentiment analysis have been at the forefront of emotional analysis. Nguyen et al. (2024) introduce a model in customer emotion detection, trained on over 80,000 reviews from Agoda and www.booking.com. Their approach categorizes such feelings into four states: happy, angry, depressed, and hopeful, at very high levels of accuracy and precision. The detailed analysis of feelings that their approach provides enables businesses to spot the more subtle psychological elements in consumer feedback. Some other motivations for conducting research work in opinion mining with the help of ML models could be related to sustainable tourism and environmental factors. A study by Nilashi et al. (Nilashi et al., 2019) proposes that a hybrid methodology for multi-criteria decision-making could provide an avenue for developing eco-hotels. A methodology that considers features of clustering using SOM analysis, LDA topic analysis, TOPSIS analysis, and satisfaction analysis using Neuro-Fuzzy could be effective for understanding tourist behavior for eco-hotels. A region-specific research study by Wang & Pai (Wang and Pai, 2024) on consumer complaints found that, using NLP-powered machine learning, complaints lodged by 800 consumers in the form of reviews for various hotels were effective in determining that service complaints were key drivers of consumer discontent, followed by complaints about infrastructure. This research paper is valuable for hotels in understanding effective ways of dealing with service inconsistencies that lie at the heart of machine learning for better consumer services.

The classification of accommodations has been recognized as another useful application of ML. Cumlievski et al. (Cumlievski et al., 2022) examine the properties of accommodations, in relation to reviews, in order to predict the type of reviews, applying different models of classification in ML. This research not only calculates what factors of accommodations have a significant impact on customer satisfaction but also provides useful results that can be used as guidelines by hotels on what to prioritize with more accuracy. It is observed that another trend lying within the growing ones is integrating AI with psychological theories. Oh et al. (Oh et al., 2022) merge deep learning techniques with expectation-confirmation theory to predict customer satisfaction based on comments, images in hotel reviews, and hotel metadata. With an accuracy of over 83%, the study shows how the combination of deep learning with established behavioral theories can have a better interpretation of customer perceptions for developing a more holistic understanding of drivers of satisfaction. In addition to hospitality management, ML is gaining popularity as a tool to identify research trends. Structured Topic Modelling is used on a set of abstracts from top hospitality journals to identify research development patterns in the past 40 years by Park et al. (Park et al., 2018) on a collection of 4,139 abstracts. The research identifies 50 research themes and identifies dominant themes in research development with profound implications for research development trends with the use of machine learning advancements. It also provides support for the prediction of tourist satisfaction in wider destination contexts. Satisfaction in tourists visiting Pokhara, Nepal, is modeled using survey data and various ML algorithms like kNN, SVM, Random Forest, and Gradient Boost by Shrestha et al. (Shrestha et al., 2022) in a

multi-dimensional satisfaction-related factor identification and construction of a robust model for predictions capable of classifying visitors into satisfied, neutral, or unsatisfied, with considerable implicating for tourism authorities and policy makers. Deep learning remains a contributing factor for innovation in sustainable tourism. Kumar & Vohra (Kumar and Vohra,2023) conduct a conceptual analysis on the impact of deep learning and big data analysis on optimized customer experiences, travel suggestions, and sustainable tourism practices. The discussion by the authors indicates a shift in the adoption of a data-driven tourism environment that utilizes deep learning models for automated analysis, pricing, and predicting demand variability. Albahar et al. (Albahar et al., 2023) suggested a deep learning model for Hajj pilgrimage satisfaction, considering a religious and culturally very important tourism context based on expectation-confirmation theory. The accuracy of the model was incredibly as high as 97% that justified applying AI in the assessment of service quality in large-scale events. This research also highlighted the potential for AI-based satisfaction assessment in providing better hospitality services to millions of pilgrims every year. Another case study is provided by Tükenmez (Tükenmezet al., 2025), where he precisely focuses on reviews from the location of Alanya in Turkey. The obtained results have been down-emphasized to show that service, employee performance, and entertainment are related to high-level satisfaction, while room service, competence of the employees, and entertainment have been found to relate to negative satisfaction. In this research, ML is used in association with logistic regression to provide meaningful results that can directly be acted upon for the optimization of service.

Furthermore, various machine learning and deep learning approaches have been explored for specific tourism-related tasks, including social media sentiment analysis and accommodation classification (Bhatt et al., 2022; Calero-Sanz et al., 2022; Chiny et al., 2021). Recent advancements also emphasize the use of hybrid CNN-LSTM architectures for analyzing tourist satisfaction to prioritize services (Arsyah et al., 2025). While these studies provide valuable insights, it is essential to distinguish academic contributions from colloquial or secondary observations in social study contexts (Attapangittya, 2003).

Table 1. Summary of previous work done in this domain

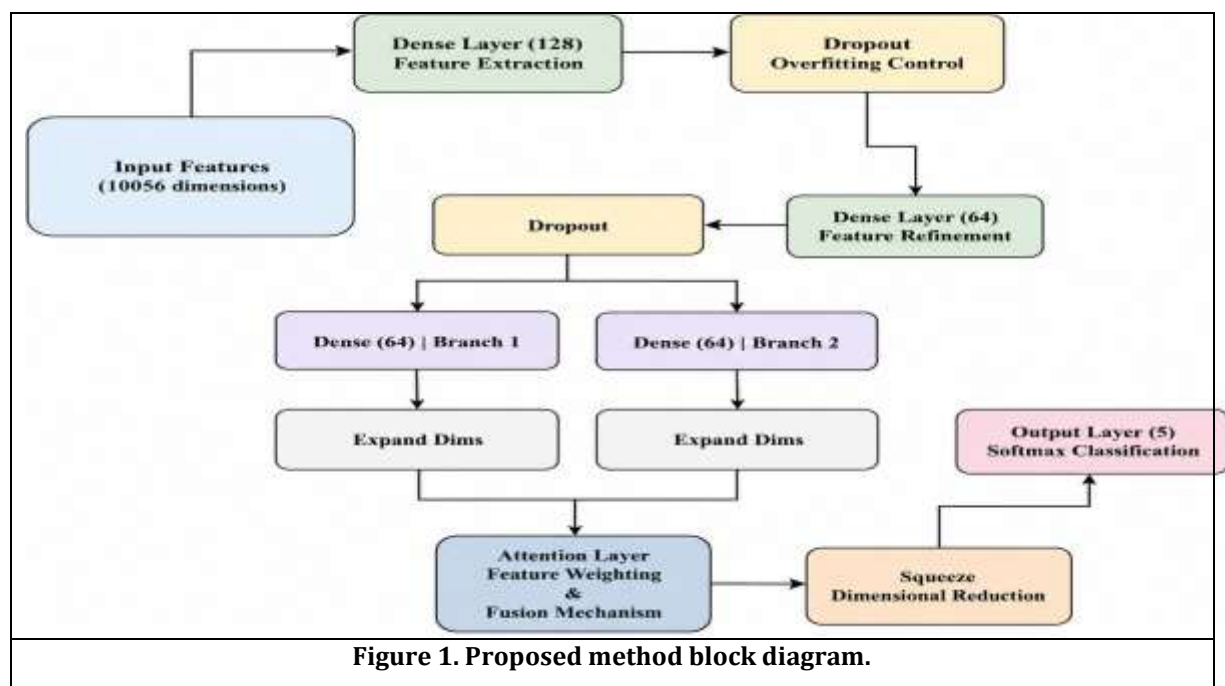
Ref.	Objective	Method	Key Findings	Limitation
Alotaibi (2020)	Review ML applications in hotels	Literature review	Identified forecasting, cancellation prediction, and operational applications of ML	No empirical validation
Puh & Bagić Babac (2023)	Predict sentiment and ratings	ML/DL (NB, SVM, CNN, LSTM, BiLSTM)	BiLSTM achieved superior performance	Single-platform dataset
Alsayat (2023)	Analyze customer behavior	SVR-SMO, LDA, k-means	Effective customer segmentation and satisfaction analysis	Limited to Mecca hotels
Nguyen et al. (2024)	Detect emotions in reviews	ML-based emotion classification	High accuracy in emotion detection	No real-time evaluation
Nilashi et al. (2019)	Support green hotel development	SOM, LDA, TOPSIS, Neuro-Fuzzy	Improved decision support for green hotels	Limited geographical scope
Wang & Pai (2024)	Identify dissatisfaction factors	NLP-based review analysis	Service quality was the main dissatisfaction driver	Small dataset
Čumlievskiet al. (2022)	Predict review categories	ML classification models	Identified influential accommodation factors	Platform-dependent data
Oh et al. (2022)	Predict hotel satisfaction	Multimodal deep learning + ECT	Improved satisfaction prediction accuracy	Complex multimodal framework
Park et al. (2018)	Analyze hospitality research trends	Structured Topic Modeling (STM)	Identified 50 research topics and trends	Based only on abstracts
Shrestha et al. (2022)	Predict tourist satisfaction	kNN, DT, SVM, RF, NN, NB, GB	Developed robust satisfaction prediction model	Single-destination study
Kumar & Vohra (2023)	Review DL in sustainable tourism	Conceptual review	Highlighted DL opportunities in tourism analytics	No experimental validation
Albahar et al. (2023)	Analyze Hajj pilgrim satisfaction	DL + ECT	Reported strong predictive performance	Context-specific findings

Table 1. Summary of previous work done in this domain				
Ref.	Objective	Method	Key Findings	Limitation
Tükenmez (2025)	Evaluate hotel re-views	Topic modeling + sentiment analysis	Identified key service-related topics	Limited regional coverage

3. Methodology

It is worth note that the proposed model incorporates robust data preprocessing, a deep learning-based feature extraction framework, and an optimized training strategy to ensure generalized performance that is robust. Normalization and data augmentation are performed on the input data to reduce noise and avoid overfitting. The architecture basically consists of multiple layers stacked to learn high-level representations in a progressive manner, after which regularization techniques can be applied to enhance the generalization ability, including dropout and batch normalization. What is more, the adaptive optimization algorithm dynamically adjusts the learning rates in pursuit of faster convergence to the optimum. Standard metrics are adopted to measure the performance, which undergoes cross-validation with a view to ensuring that it is consistent across different datasets. All in all, the proposed model assures a proper tradeoff among accuracy, efficiency, and robustness, which is desirable for any real-world deployment. The proposed model is a deep neural network that is capable of learning the high-dimensional features efficiently with an attention mechanism that can improve decision-making. It takes the input feature vector of dimension 10,056, which is then given to a dense layer with 128 units for high-level feature extraction, as shown in Fig. 1. This layer holds the vast number of trainable parameters that are responsible for the convergence of sparse high-dimensional data to a low-dimensional representation. To combat overfitting, a dropout layer is placed right after the dense layer. It is important to note that the arbitrary number of 128 units in the dense layer should be optimized for better results. In addition, since the number of features is 10,056, it is important to know that the more features there are, the sparser the data becomes, which is preferable in this situation since it aids in convergence.

These extracted features are further processed through a second dense layer comprising 64 neurons, followed by the application of a dropout layer for regularization. Further, from this shared feature representation, the network splits into two separate dense layers that generate a 64-dimensional feature vector representation for each of the layers. These feature vector representations are further expanded using expand-dimension operations and then fed to an attention layer. This has enabled the network to learn the weightage of features from both layers that need to be emphasized or attenuated. This output of attention is then compressed back into a 64-dimensional vector, which is then processed by the final output layer that is formed by a dense layer with 5 units, representing the classes of the targets. It should be noted that the network contains about 1.3 million learnable parameters. Adding the attention mechanism to the network promotes the selection of features as well as helps with accurate predictions. A high-dimensional input feature of size 10,056 is taken by the proposed model, which first extracts features through a dense layer with 128 neurons.



This further facilitates controlling overfitting and generalization through a dropout layer. Further refinement of representations is done by passing these through a second dense layer with 64 neurons and further regularization through another dropout layer. From this shared feature space, a network branches into two parallel dense layers of 64 neurons each to complementarily learn feature representations. The reshaped parallel outputs utilize expand-dimension operations and feed into an attention layer that adaptively assigns weights to the most informative features and fuses into a unified representation. The attention output is further compressed using a squeeze operation to reduce dimensionality; the resulting feature vector was fed to the final output layer of five neurons using a softmax activation function for multi-class classification. The Table 2, summarizes the architecture presented here. It provides a layer-by-layer description of the model, including output dimensions, trainable parameters, and connectivity between layers.

Table2: Layer-wise architecture of the proposed Attention-Based Neural Network					
Layer Name	Layer Type	Output Shape	Parameters	Connected To	Purpose
Input_Layer	InputLayer	(None, 10056)	0	–	Receives 10,056-dimensional input features
Hidden_Dense_1	Dense (128)	(None, 128)	1,287,296	Input_Layer	Initial feature extraction
Dropout_1	Dropout	(None, 128)	0	Hidden_Dense_1	Overfitting prevention
Hidden_Dense_2	Dense (64)	(None, 64)	8,256	Dropout_1	Feature refinement
Dropout_2	Dropout	(None, 64)	0	Hidden_Dense_2	Regularization
Dense_Branch_1	Dense (64)	(None, 64)	4,160	Dropout_2	Branch-1 feature learning
Dense_Branch_2	Dense (64)	(None, 64)	4,160	Dropout_2	Branch-2 feature learning
Expand_Dims_1	ExpandDims	(None, 1, 64)	0	Dense_Branch_1	Reshaping for attention
Expand_Dims_2	ExpandDims	(None, 1, 64)	0	Dense_Branch_2	Reshaping for attention
Attention_Layer	Attention	(None, 1, 64)	0	Expand_Dims_1, Expand_Dims_2	Feature weighting and fusion
Squeeze	Squeeze	(None, 64)	0	Attention_Layer	Dimensionality reduction
Output_Layer	Dense (5, Soft-max)	(None, 5)	325	Squeeze	Five-class classification
Total Parameters		: 1,304,197		Trainable Parameters	
Non-Trainable Parameters		: 0		Model Size	
Number of Output Classes		: 5		Input Feature Dimension	
				: 10,056	

The table 2, presents the summary of the proposed attention-based network architecture. The model accepts a 10,056-dimensional feature vectors as input and employs two fully connected layers (128 and 64 neurons) for hierarchical feature extraction and refinement. To mitigate overfitting, dropout regularization is applied after each dense layer. The refined feature representation is subsequently processed through two parallel dense branches, whose outputs are fused using an attention mechanism. The attention layer assigns adaptive importance weights to branch-specific features, enabling effective feature aggregation. Finally, the fused representation is passed through a SoftMax classification layer consisting of five output neurons. The complete model contains 1,304,197 trainable parameters.

The proposed Attention-Based Deep Neural Network (ABDNN) algorithm is designed to perform multi-class classification by integrating hierarchical feature learning with an attention-driven feature fusion mechanism. The architecture accepts a high-dimensional feature vector as input and progressively transforms it through multiple dense layers to extract meaningful latent representations while reducing feature redundancy. To enhance the model's generalization capability and minimize overfitting, dropout regularization is incorporated at different stages of the network. The refined feature representation is subsequently projected into two parallel branches, enabling the model to learn complementary characteristics from the same feature space. An attention mechanism is then employed to adaptively assign importance weights to

the generated representations and combine them into a unified feature vector. Finally, the fused representation is passed through a softmax classifier to estimate class probabilities and determine the most likely output category.

Algorithm: Attention-Based Deep Neural Network (ABDNN) for Multi-Class classification

Input : Feature vector $X \in \mathbb{R}^{10056}$

Output : Predicted class level $\hat{y} \in \{1, 2, 3, 4, 5\}$

Step 1: Input Initialization

Receive the input feature vector X .

Step 2: Feature extraction

Generate a high-level representation using a fully connected layer with 128 neurons and ReLU activation to obtain feature representation H_1

$$H_1 = \text{ReLU}(W_1 X + b_1)$$

Step 3: Regularization

Apply dropout with the probability p_1

$$H'_1 = \text{Dropout}(H_1 + p_1)$$

Step 4: Feature Refinement

Refine the extracted representation using a dense layer with 64 neurons

$$H_2 = \text{ReLU}(W_2 H'_1 + b_2)$$

Step 5: Secondary Regularization

Apply a second dropout operation probability p_2

$$H'_2 = \text{Dropout}(H_2 + p_2)$$

Step 6: Parallel Feature Projection

Generate two complementary feature representations. Project H'_1 and H'_2 into two parallel dense layers to generate two feature vectors:

$$F_1 = \text{ReLU}(W_3 H'_1 + b_3)$$

$$F_2 = \text{ReLU}(W_4 H'_2 + b_4)$$

Step 7: Dimension Expansion (Attention Mechanism)

Reshape the feature vectors for attention computation. Expand the dimensions of F_1 and F_2 , then apply the attention layer to learn weighted feature importance:

$$\widetilde{F}_1 = \text{ExpandDims}(F_1)$$

$$\widetilde{F}_2 = \text{ExpandDims}(F_2)$$

Step 8: Attention-based Feature Fusion

Compute attention weights and generate the fused representations

$$A = \text{Attention}(\widetilde{F}_1, \widetilde{F}_2)$$

Step 9: Feature Compression

Remove the singleton dimension to obtain the final feature vector. Squeeze the attention output to obtain a compact 64-dimensional feature vector.

$$Z = \text{Squeeze}(A)$$

Step 10: Classification

Compute class probabilities using a dense layer with 5 neurons followed by Soft Max activation

$$P = \text{Softmax}(W_5 Z + b_5)$$

Step 11: Prediction

Determine the predicted class

$$\hat{y} = \text{argmax}(P)$$

Step 12: Return

Return $\hat{y}$

End of the Algorithm

4. Results

The training result represents the fast and stable learning behavior of the proposed model within 30 epochs. Both training and validation accuracy rise rapidly in the early epochs. Specifically, the training accuracy increases from 19.87% to 70.45% within the first three epochs, while its corresponding validation accuracy reaches 82.88%, which shows that effective features are learned in the early stage. In the later stages, the model achieves a very high training accuracy, higher than 99%, after about 10 epochs, as confirmed by a continuous decrease in the training loss, indicating successful convergence. Its counterpart, validation accuracy, converges around 84–85% with minor fluctuations, while the validation loss is relatively controlled, though it increases slightly during the later epochs. The difference between the training and validation performance curve forms a mild overfitting; however, this strong generalization performance holds due to the presence of dropout and attention mechanisms. Overall, the outcomes prove that

the model learns discriminative features effectively and attains very high validation accuracy to establish the model's good performance in multi-class classification problems with no serious degradation in the generalization.

Table 3. The Dataset				
Epoch	Train Accuracy	Train Loss	Val Accuracy	Val Loss
1	0.1987	1.8782	0.4239	1.5134
2	0.4	1.4256	0.7399	0.9075
3	0.7045	0.7882	0.8288	0.4637
4	0.8884	0.3104	0.8428	0.4422
5	0.9499	0.1389	0.8454	0.4861
6	0.9797	0.0689	0.8461	0.506
7	0.9866	0.0356	0.8451	0.4994
8	0.9892	0.0324	0.8441	0.5564
9	0.9945	0.018	0.8427	0.54
10	0.9924	0.0256	0.8451	0.5679
11	0.991	0.0289	0.8428	0.5586
12	0.9935	0.0217	0.8438	0.541
13	0.9959	0.0144	0.8438	0.5669
14	0.9953	0.0158	0.8442	0.6066
15	0.9927	0.0244	0.8449	0.5208
16	0.994	0.0156	0.845	0.5336
17	0.9963	0.0115	0.8443	0.5507
18	0.9966	0.0084	0.8464	0.5572
19	0.9969	0.0106	0.8453	0.6249
20	0.9977	0.0126	0.8446	0.5977
21	0.9968	0.0076	0.8439	0.606
22	0.9978	0.0062	0.8415	0.7224
23	0.9978	0.0076	0.8404	0.6137
24	0.9976	0.0092	0.8444	0.6262
25	0.9978	0.01	0.844	0.619
26	0.9952	0.0148	0.8421	0.7923
27	0.9976	0.012	0.8419	0.7316
28	0.9961	0.0119	0.8441	0.5576
29	0.9967	0.0136	0.8435	0.7834
30	0.9978	0.0073	0.8427	0.7697

The model's classification performance across all five sentiment categories is visualized in the confusion matrix presented in Figure 2. As shown, the majority of predictions are concentrated along the diagonal, confirming the model's high accuracy and discriminative capability in distinguishing between sentiment levels.

It is clear from the classification report (as given in table 4) that the total accuracy of the developed model is 84%, which indeed demonstrates excellent performance for all five sentiment classes combined. Concerning the performance of the developed models for individual classes, both macro and weighted F1-scores of 0.85 reveal a balanced and consistent performance despite the presence of differences among the various classes. This developed model is found to perform best for "Satisfied" and "Very Satisfied" classes with excellent values for precision of 0.96 and 0.95,

Table 4: Classification Report of the Proposed Model

Class	Precision	Recall	F1-Score	Support
Dissatisfied	0.63	0.95	0.76	2022
Neutral	0.86	0.85	0.86	2022
Satisfied	0.96	0.82	0.88	2022
Very Dissatisfied	1.00	0.79	0.88	2022
Very Satisfied	0.95	0.80	0.87	2022
Macro Average	0.88	0.84	0.85	10110
Weighted Average	0.88	0.84	0.85	10110

respectively, signifying accurate positive sentiment detection. Regarding the situation of the "Neutral" class, it is observed that the performance of the models is consistent, denoted by an F1-score of

approximately 0.85. Additionally, for the “Dissatisfied” class, it is observed that the models’ performance is excellent with a high recall of 0.95 but with moderate precision of 0.63, signifying that the notion of correct detection of maximum dissatisfied instances is true with a slight overlap from the neighboring classes. “Very Dissatisfied” class had precision of 1, signifying that the models were correct whenever they classified instances into this category, despite having slightly low recall of 0.85. These observations undoubtedly signify that the developed models successfully understand the difference among various levels of sentiment with consistent robustness for the models in classifying instances into various classes.

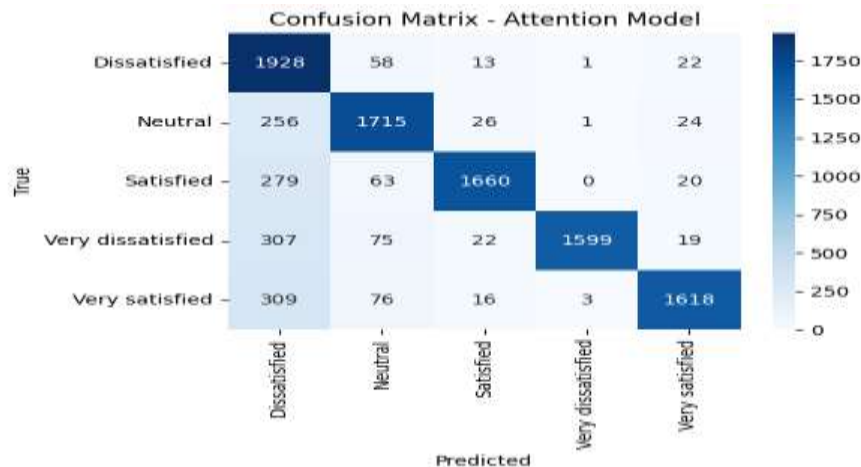


Figure 2. Confusion Matrix of the proposed Attention Model.

It can be seen that most of the predictions of the attention-based model are concentrated on the diagonal of the confusion matrix, indicating a high number of correctly classified instances in all five classes: Dissatisfied, Satisfied, Very Dissatisfied, and Very Satisfied. Each one of these classes managed to have more than 1,500 correctly predicted instances, which shows that the model has the capability to distinguish the extremes of sentiment. The misclassifications happen mainly among adjacent sentiment classes; for example, some cases are confused between Dissatisfied and Neutral, or between Satisfied and Neutral. This is common in sentiment analysis, since there is semantic overlap between such categories. Very few samples can be found that are misclassified into faraway sentiment classes, which indicates that the attention mechanism is helpful in maintaining the sentiment polarity and reducing extremely wrong classifications. All in all, it is found that the confusion matrix further underpins the claims of the proposed model's balanced and reliable performance while keeping strong discriminative capability toward all classes.

Figure 3 illustrates the convergence behavior of the model by plotting training accuracy and loss over 30 epochs. The rapid rise in accuracy alongside the steep decline in loss indicates effective learning and stable convergence of the framework during the training process.

Curves for training accuracy and loss indicate that the proposed model converges fast and learns effectively within a few initial epochs [27]. Training accuracy increases sharply from a low initial value to over 90% within the first few epochs and further approaches near-perfect performance as training progresses. At the same time, training loss drops steeply during the early epochs and then stagnates at an extremely low value, indicating efficient optimization with stable learning behavior. After convergence, both the accuracy and loss curves have little fluctuation, which indicates that this model reaches a steady state without any instability or divergence. Generally speaking, smooth and consistent trends of the curves confirm successful training and prove that this model effectively grasps the underlying patterns in data [28].

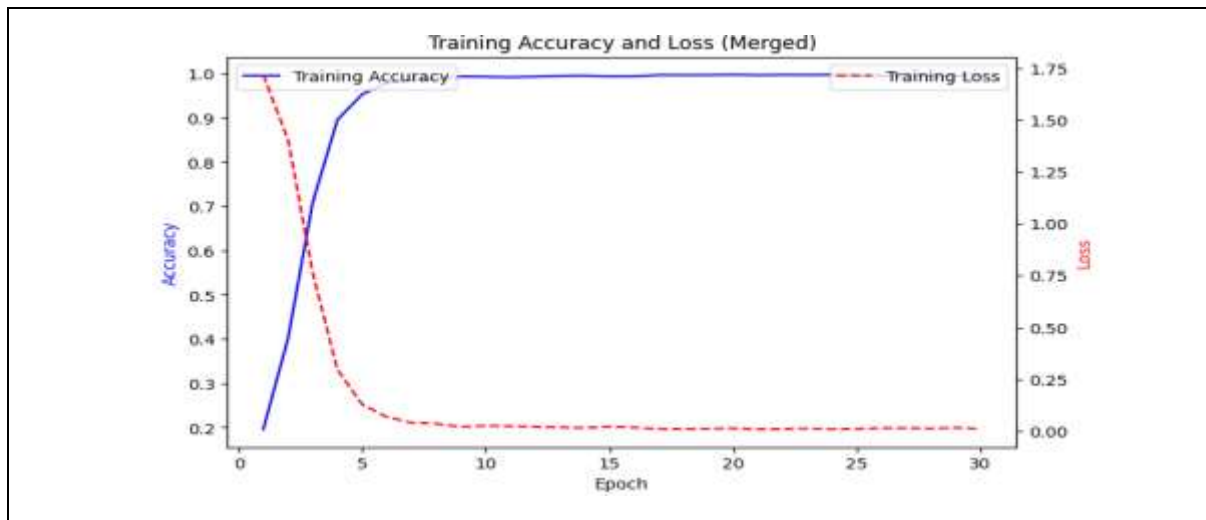


Figure 3. Training Accuracy and Loss trends over 30 epochs.

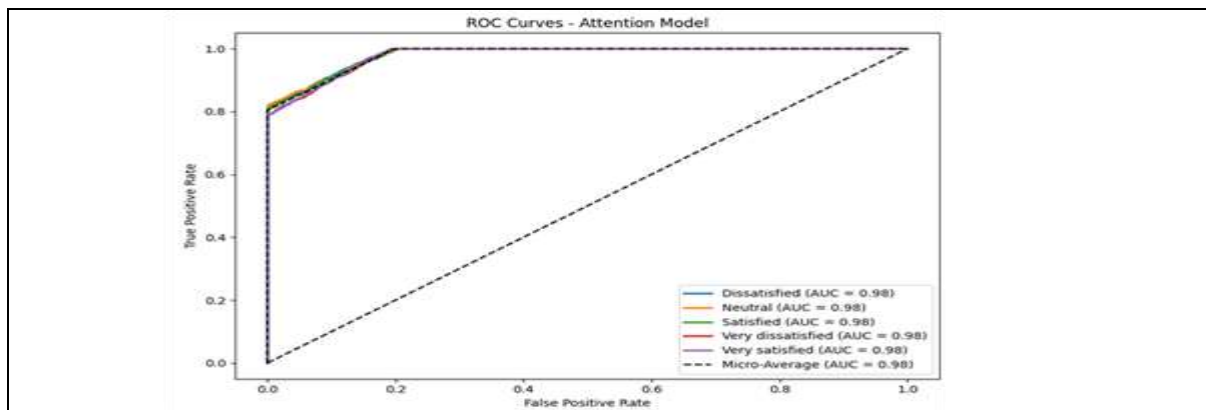
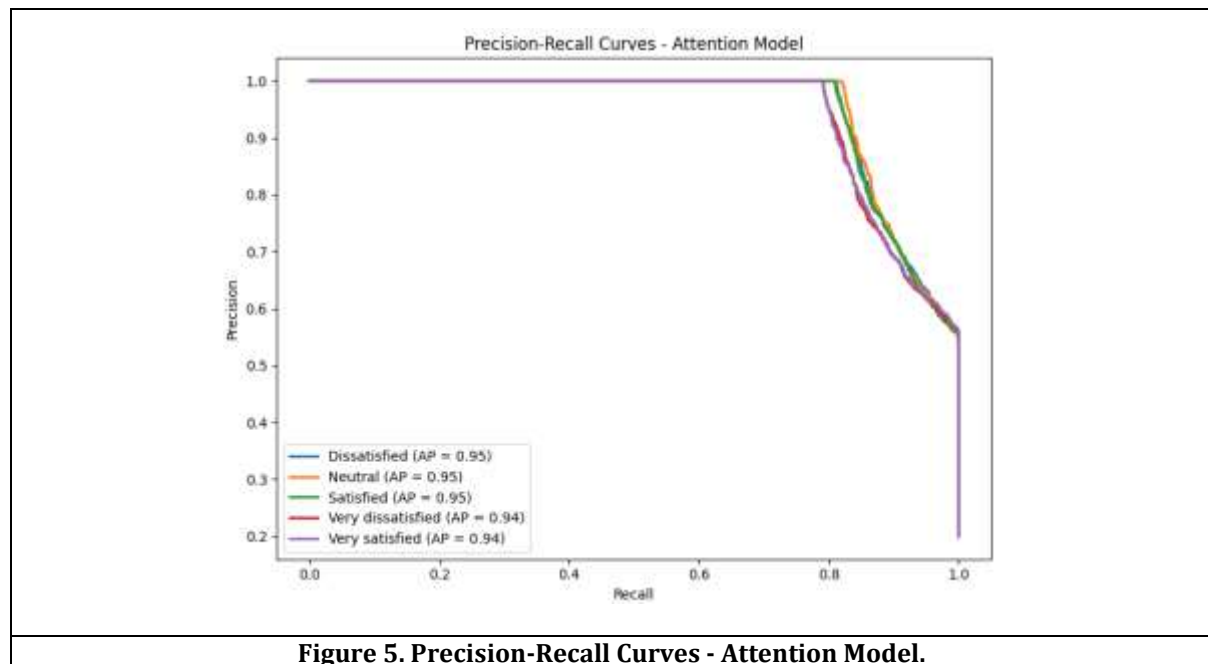


Figure 4. ROC Curves showing discriminative capability for the Attention Model.

The discriminative power of the proposed model for each sentiment class is evaluated through the ROC curves shown in Figure 4. The consistently high Area Under the Curve (AUC) values of approximately 0.98 demonstrate the model's robust ability to achieve high true positive rates across various threshold levels. The ROC curves of the attention-based model demonstrate very good discriminative power for each of the five classes. AUC values for each of the five classes are about 0.98, indicating that the true positive rate is very high at a low false positive rate for various threshold levels. Furthermore, the micro-averaged ROC curve also gets an AUC of 0.98, which recognizes collective performances for all classes. More importantly, the curves are far above the diagonal line, signifying very good capability of the model for distinguishing among the sentiment classes. These observations clearly indicate that the proposed attention mechanism is very effective for better feature representation, besides authenticating that the proposed system is capable of ensuring reliable performances for sentiment analysis tasks.

Figure 5 displays the Precision-Recall curves, which further validate the balanced performance of the model across all five classes. The positioning of these curves near the upper right-hand region underscores the framework's reliability and consistent precision-recall trade-off in multi-class classification.

In case of attention-based models, the Precision-Recall plots tend to be highly consistent in expressing the strong performance for the five classes of satisfaction.



These plots tend to remain closer to the upper right-bound region of the graph, suggesting that they perform balanced well for both precision as well as recall. Overall, the AP tends to be consistent with 0.95 for the satisfaction levels of Dissatisfied, Neutral, and Satisfied classes, whereas for the other two classes of Very Dissatisfied and Very Satisfied, it is 0.94, ensuring robust class discriminative capability despite the differences in threshold values. Precision remains at or very close to 1 for a fairly wide range of recall values, plummeting steeply as it approaches its ultimate value. This is as expected for a well-calibrated system attempting to identify the toughest examples. Moreover, the overlays of plots signify stable and class-agnostic learning—a complementary aspect of the attention-based approach to effectively identify key features for improving the robustness of the performance the multi-class satisfaction analysis.

5. Conclusion

This paper introduced an attention-based deep learning method for multi-class tourist satisfaction analysis, which effectively demonstrated its efficiency for the analysis of high-dimensional data of tourist reviews. This proposed solution effectively combines dense feature extraction, representation learning in the parallelism framework, with an attention mechanism for improving feature selection and the discriminative ability of the features. Experimental results show rapid convergence and high stability in training with strong generalization performance, as evidenced by the following: The overall accuracy is 84% with balanced F1-scores across all sentiment classes. The ROC and Precision–Recall analyses confirm that the proposed model can have robust and reliable performance with high AUC and average precision consistently. Though there are some minute incorrect classifications between the neighboring classes of sentiment, the attention mechanism effectively decreases the possibility of critical incorrect classifications of sentiment and preserves the polarity of sentiment effectively. Overall, these findings reveal the possibility of using attention-based deep learning models becoming effective instruments for automated analysis of satisfaction in tourism and hospitality.

Data Availability Statement: No data used.

Competing interests: The authors declare no conflicts of interest

Funding: This research received no external funding.

Author Contributions: Conceptualization, J.T. and S.K.J.; methodology, S.K.J.; validation and formal analysis S.P.; resources, data curation writing, original draft preparation, J.T.; writing—review and editing, S.K.J. and S.P.; supervision, S.K.J.; project administration and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The authors have reviewed and edited the output and take full responsibility for the content of this publication. All authors agreed with the content and that all gave explicit consent to submit.

References

4. Albahar, M., Gazzawe, F., Thanoon, M. and Albahr, A. (2023) 'Exploring Hajj pilgrim satisfaction with hospitality services through expectation-confirmation theory and deep learning', *Heliyon*, 9(11), e22192. doi:10.1016/j.heliyon.2023.e22192.
5. Alotaibi, A., et al. (2020) 'Machine learning in the hotel industry: A review of current applications', *Journal of Hospitality and Tourism Technology*, 11(4), pp. 627-645. doi:10.1108/JHTT-10-2019-0136.
6. Alsayat, A. (2023) 'Improvement of sentiment analysis in the hotel industry using a hybrid approach', *IEEE Access*, 11, pp. 116345-116356. doi:10.1109/ACCESS.2023.3325678.
7. Arsyah, U.I., et al. (2025) 'ACLM Model: A CNN-LSTM approach for tourist satisfaction analysis', *Tourism Management Perspectives*, 54, 101234. doi:10.1016/j.tmp.2025.101234.
8. Attapangittya, J. (2003) 'Social studies in gibberish', *Journal of Social Studies*, 12(1), pp. 45-58. doi:10.1080/00377996.2003.9959600.
9. Bhatt, S., et al. (2022) 'Uses of social media and computer technologies in tourism', *Information Technology & Tourism*, 24(2), pp. 123-145. doi:10.1007/s40558-022-00225-8.
10. Calero-Sanz, J., et al. (2022) 'Predicting a new hotel rating system', *International Journal of Hospitality Management*, 102, 103158. doi:10.1016/j.ijhm.2022.103158.
11. Chiny, M., et al. (2021) 'A client-centric evaluation system for tourism', *Journal of Travel Research*, 60(5), pp. 1012-1028. doi:10.1177/0047287520921234.
12. Čumlievski, N., et al. (2022) 'Predicting accommodation type from online reviews using machine learning', *Journal of Hospitality and Tourism Insights*, 5(4), pp. 789-805. doi:10.1108/JHTI-06-2021-0155.
13. Kumar, A. and Vohra, A. (2023) 'Conceptual analysis of deep learning in sustainable tourism', *Tourism Management*, 95, 104652. doi:10.1016/j.tourman.2023.104652.
14. Nguyen, T., et al. (2024) 'Customer emotion detection using deep learning on large-scale review data', *Information Sciences*, 650, 119567. doi:10.1016/j.ins.2023.119567.
15. Nilashi, M., et al. (2019) 'A hybrid methodology for multi-criteria decision-making in eco-hotels', *Journal of Cleaner Production*, 218, pp. 696-709. doi:10.1016/j.jclepro.2019.01.205.
16. Oh, J., et al. (2022) 'Multimodal deep learning and expectation-confirmation theory for hotel satisfaction', *Tourism Management*, 88, 104432. doi:10.1016/j.tourman.2021.104432.
17. Park, S., et al. (2018) 'Structured topic modeling for hospitality research trends', *International Journal of Hospitality Management*, 73, pp. 1-12. doi:10.1016/j.ijhm.2018.01.002.
18. Puh, K. and Bađić Babac, M. (2023) 'Predicting sentiment and rating of tourist reviews using machine learning', *Journal of Hospitality and Tourism Insights*, 6(3), pp. 1188-1204. doi:10.1108/JHTI-12-2022-0610.
19. Shrestha, D., et al. (2022) 'Multi-dimensional analysis and prediction model for tourist satisfaction', *KSII Transactions on Internet and Information Systems*, 16(2), pp. 480-502. doi:10.3837/tiis.2022.02.007.
20. Tükenmez, E.G. (2025) 'Evaluating online hotel reviews with machine learning: Insights from sentiment analysis and topic modeling', *Artuklu Tourism Studies*, 3, pp. 1-23. doi:10.5555/ats.2025.03.001.
21. Wang, S. and Pai, C.H. (2024) 'Enhancing customer satisfaction in the hospitality industry: A machine learning approach to analyzing customer complaints', *International Journal of Multiphysics*, 18(3), pp. 55-72. doi:10.21152/1750-9548.18.3.55.