Vol. 2 No. 4 (2024)

Spectrum of Engineering Sciences

SPECTRUM OF ENGINEERING SCIENCES

Online ISSN
3007-3138
Print ISSN
3007-312X

Criticality and Security Evaluation of Events: Insights for Luxury Hotel Management

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Abstract

In this research paper, we present a comprehensive Business Intelligence (BI) framework tailored specifically for luxury hotels to optimize their digital marketing strategies through sentiment analysis of customer reviews. By employing advanced Machine Learning (ML) and Deep Learning (DL) methods, we aim to provide valuable insights into customer sentiments to accurately classify sentiments into positive and negative polarities. We utilize Support Vector Machine (SVM), Random Forests (RF), Naive Bayes classifier (NB), and long short-term memory networks (LSTM) networks to effectively classify insights derived from hotel reviews. To begin, we initially perform data acquisition, followed by the identification of implicit and explicit features, and finally, sentiment classification. To evaluate the performance of our approach, we measure precision, recall, True Positive Rate (TPR), False Positive Rate (FPR),

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3007-3138
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loss, and validation accuracy. Substantially, we conduct a comprehensive comparison of different regularization and optimization methods. Our proposed framework demonstrates exceptional accuracy, particularly on the LSTM network, when compared to SVM, RF, and NB classifiers. This outstanding accuracy establishes the superiority of our approach in effectively categorizing hotel review sentiments.

Index Terms: Sentiment Analysis, security evaluation Review Classification, Luxury hotel Reviews, Smart marketing, Business intelligence, Machine Learning.

Introduction

In recent years, the hospitality sector widely depends upon customer feedback and evaluations as they are instrumental in gauging consumer satisfaction levels and eventually help in strategic planning. The emergence of social media has made it less complicated for consumers to express their opinions through reviews about luxury hotels. A subset of natural language processing (NLP), namely sentiment analysis or opinion mining is used extensively to ensure the automatic detection of sentiments or viewpoints mentioned within the text body [1-3]. Luxury hotel reviews use sentiment analysis by examining and commonly categorizing individuals shared experiences into positive, negative, or neutral categories providing greater insight into guest experience and level of contentment. Deep Learning Models which use algorithmic functions and statistical methods help isolate patterns from collected data and enable predictions related to categorized sentiments. Sentiment analysis further empowers hoteliers by giving them valuable information which can be used towards improving offerings and enhancing guest experience thus making informed decisions about future growth. It helps hoteliers to effectively track and analyze customer feedback.

Sentiment analysis automates the process of reading and categorizing each review rather than doing it by hand, saving time and effort while delivering reliable and objective outcomes. Furthermore, sentiment analysis can be used to spot recurring problems and new trends in the world of luxury hotels [5-6,9]. Hotel management can also learn more about the components of their operations that are evoking positive or negative sentiments by extracting emotive information from reviews. This information can direct targeted upgrades and enhancements, increasing the pleasure and loyalty of

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Online ISSN
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the customer. Substantially, benchmarking and comparison among other luxury hotels are made possible through sentiment analysis. The Hoteliers can pinpoint market trends, competitive advantages, and areas where their property excels or needs to be improved by examining customer sentiment across several locations. This competitive intelligence can influence marketing tactics, pricing choices, and general market positioning [10]. The sentiment analysis of reviews of luxurious hotels is largely driven by deep learning models. These models are developed using labeled datasets, where a group of reviews is given sentiment classifications by human experts. Naive Bayes, Random Forest, Support Vector Machines (SVM), and Recurrent Neural Networks (RNN) are among the popular machine learning techniques for sentiment analysis [11-16]. These models can accurately classify new, unseen reviews into sentiment categories after learning from the labeled data and doing so with a large amount of data. The richness of natural language and the nuanced nature of consumer sentiments provide difficulties in luxury hotel review sentiment analysis. Luxury hotel evaluations frequently include figurative language, complex idioms, and industry-specific lingo. Such reviews require complex NLP techniques and specialized topic expertise to comprehend the context and accurately interpret the sentiments.

Motivation and Contributions

In this research, we use machine learning models to do sentiment analysis on reviews of luxury hotels [15, 16]. Our objective is to create a reliable and accurate system that can sort reviews according to sentiment and offer insightful information to the management of luxury hotels. We will use labeled datasets, including various evaluations of luxury hotels, to train and test several machine-learning algorithms. We will determine the best method for sentiment analysis in the luxury hotel area by comparing and analyzing the performance of different models.

The remaining section of this paper is structured as follows: The sentiment analysis work that has been done in the past and its uses in the hospitality sector are summarized in Section 2. The datasets, preprocessing techniques, and machine learning models applied in this research are all presented in Section 3. The experimental analysis and findings are presented in Section 4. Section 5 finishes the paper and outlines potential future research topics in sentiment analysis of evaluations of luxury hotels.

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Related Work

In recent years, the SA of hotel reviews using machine learning models has drawn significant focus due to the increasing value of online consumer feedback and the necessity for hoteliers to properly comprehend and address customers' opinions. A summary of the study on SA of hotel reviews using machine learning models that were done between 2017 and 2022 will be given in this review of the literature [4-12]. It emphasizes the approaches, procedures, and significant conclusions of pertinent investigations conducted throughout this time. Various machine learning techniques have been used for the SA of hotel reviews during the reviewed time. Liu et al. [1] used Support Vector Machines (SVM) to categorize positive and negative attitudes in hotel reviews. Naive Bayes classifiers have also been extensively employed for SA in hotel reviews. Zhang et al. [2] classified hotel reviews into good, negative, and neutral attitudes using a Naive Bayes classifier, obtaining high accuracy in the process. Deep learning models [17-20] have also demonstrated impressive performance in SA of hotel reviews over this time. Ma et al. [3] suggested an LSTM-based Recurrent Neural Network (RNN) model to collect sequential information in hotel evaluations and enhanced sentiment classification accuracy. Convolutional Neural Networks (CNN) have acquired popularity for usage in SA in hotel ratings. In their sentiment classification tasks, Wang et al. [4] used a CNN model and produced competitive results. Enhancing the accuracy and dependability of SA in hotel reviews has required the use of data preprocessing techniques. Researchers have used a variety of methods, including sentiment lexicon-based feature extraction [20-23], stop-word elimination, and stemming. Yang et al. [5] applied preprocessing approaches (Yang et al., 2019) to increase the accuracy of sentiment categorization in hotel reviews, Additionally, sentiment dictionaries and domain-specific lexicons have been frequently used. Guo et al.'s [6] introduction of a sentiment vocabulary created exclusively for hotel evaluations improved SA's accuracy. The research done throughout this time has given us useful information about decision-making and hotel management. The significance of concentrating on these areas for development is highlighted by Khan et al. [7] finding that variables including the cleanliness of the room, the level of service, and the location strongly affect the sentiment expressed in hotel reviews. Moreover, in [8] reveales specific terms and phrases that were frequently linked to both

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good and negative sentiments in hotel evaluations, giving hoteliers the ability to comprehend visitor preferences and remedy problem areas. A comparative study amongst hotels has been made easier because of the use of machine learning models for SA [23-24]. Tang et al. [9] analyzed sentiment distributions across various hotel chains and found patterns and trends in client sentiments across many places to enable comparison and competitive assessment.

A hybrid recommendation system that prioritizes the needs of the customer and incorporates sentiment analysis methods were proposed by Arodh Lal et al [13]. The technology created personalized recommendations in E-Commerce applications by taking user sentiments into account. The authors use the random forest as a machine learning technique for sentiment analysis in product recommendation. The objective of the study is to predict user sentiment from customer reviews to facilitate effective product recommendations [13, 24-28]. A strategy for opinion search and pertinent product recommendations in social networks was put up by Shanmugavelu, Murugesan, and Sannasy, Muthurajkumar [15]. A stacked DenseNet121 classifier was used to analyze user feedback and make precise product suggestions [28-30]. An analysis of customer reviews for food delivery services that focused on sentiment analysis was previously carried out by Adak, Anirban, et al. [16]. They investigated how to successfully analyze and evaluate client sentiment using deep learning and understandable artificial intelligence tools. Uzbek sentiment analysis based on ratings of nearby restaurants was previously given by Matlatipov, Sanatbek, et al. [17]. They used machine learning techniques to analyze the opinions stated in reviews written in Uzbek and provide information about client preferences.

Arodh Lal et al [13] proposed a customer-centric hybrid recommendation system that integrated sentiment analysis techniques. By considering user sentiments, the system generated personalized recommendations in E-Commerce applications. The authors employ random forest as a machine learning technique for sentiment analysis in product recommendation. The study focuses on predicting user sentiment based on customer reviews to aid in effective product recommendation [11, 31,33]. Shanmugavelu, Murugesan and Sannasy, Muthurajkumar proposed a scheme for opinion search and relevant product recommendation in social networks

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[15]. They employed a stacked DenseNet121 classifier to analyze user opinions and provide accurate product recommendations. In the past, Adak, Anirban et al [16]. conducted a systematic review focused on sentiment analysis of customer reviews for food delivery services. They explored the use of deep learning and explainable artificial intelligence techniques [32-35] to analyze and interpret customer sentiments effectively. In the past, Matlatipov, Sanatbek et al [17]. presented Uzbek sentiment analysis based on local restaurant reviews. They leveraged machine learning techniques to analyze sentiments expressed in Uzbek language reviews and provide insights into customer preferences [33,37-40].

Proposed Methodology

The hybrid strategy for hotel reviews sentiment analysis using machine learning and deep learning is shown in Fig 1. The suggested methodology seeks to do sentiment analysis on hotel reviews using machine and deep learning techniques. Understanding client thoughts and sentiments expressed in hotel reviews is vital for hoteliers to make wise decisions and raise customer satisfaction. The suggested methodology combines the advantages of deep learning architectures and machine learning models to perform accurate sentiment classification and deliver beneficial insights for hotel management.

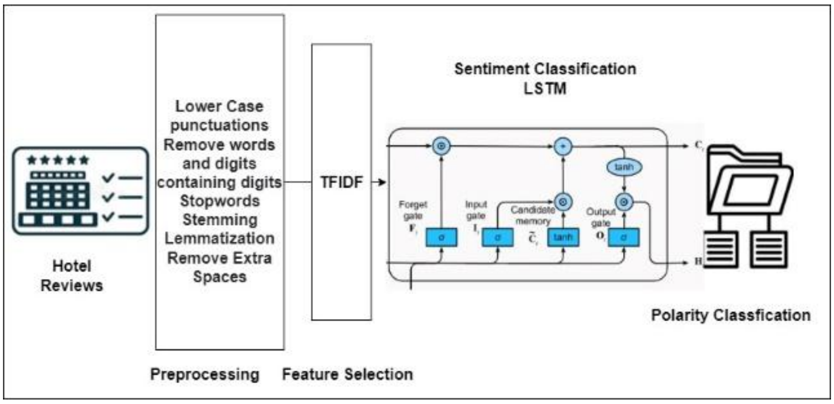

Figure 01: Hotel wise Reviews

Data Collection and Pre-Processing

The methodology's first phase includes gathering a sizable dataset of hotel evaluations from various online resources and review aggregators. The dataset should cover a variety of hotels, regions, and client experiences to ensure a full investigation as shown in Fig 2-4. When gathering and handling data, appropriate ethical issues should be considered to protect anonymity and

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privacy. After the dataset has been gathered, the text should be cleaned up and prepared for analysis using data preparation procedures. Lemmatization and stemming are two more preprocessing methods that can be used to further normalize the text. This involves removing unnecessary information, such as HTML elements and special characters, standardizing language by making it lowercase and eliminating stop words [38-40].

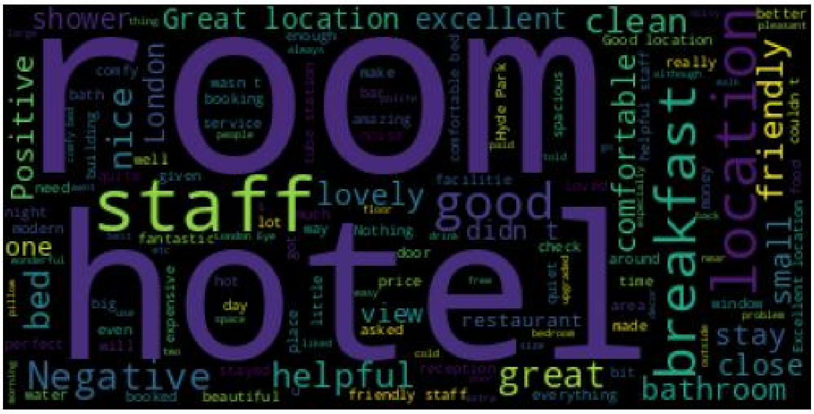

Figure 02: Most used words in Hotel Reviews

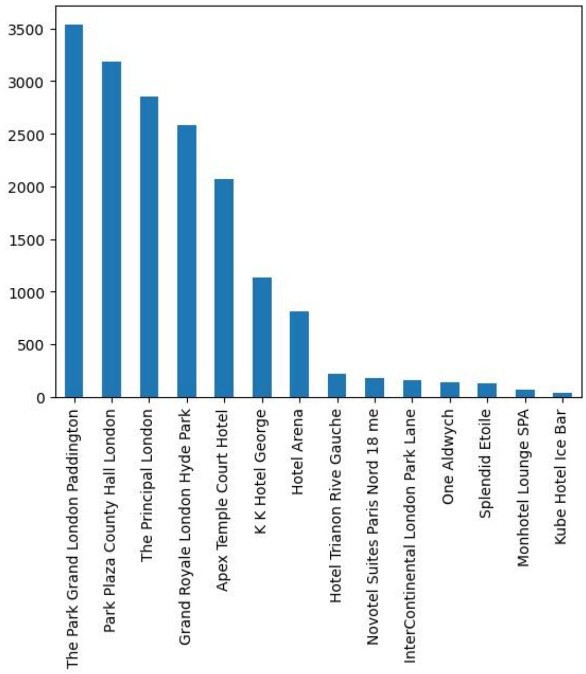

Figure 03: Hotel wise Reviews

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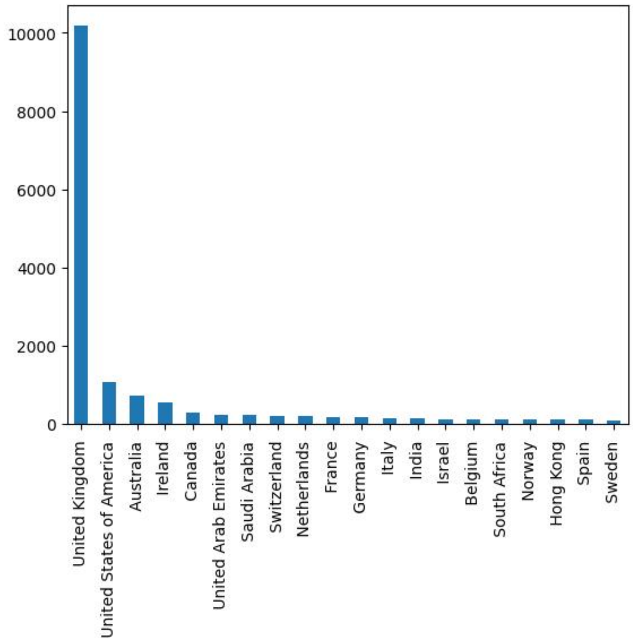

Figure 04: Nationality wise Reviews

Feature Extraction

Several strategies can be used to extract key information from hotel reviews. The Bag-of-Words (BoW) model is a popular strategy that visualizes each review as a vector of word frequencies or presence indicators. The approach known as Term Frequency-Inverse Document Frequency (TF-IDF) is another method that gives words weights based on how important they are to the review and the entire dataset.

Deep Learning Architecture

An embedding layer converts each word or sub-word in the preprocessed text into a high-dimensional vector representation. As a result, the network is better able to understand the linkages between words in the review text and their meaningful representations [3]. In one or more LSTM layers, the embedded sequences are then supplied. Multiple memory cells make up each LSTM layer, which processes sequential input and modifies internal states based on input and prior states. Three primary parts make up LSTM cells: a forget gate, an input, and an output gate. The information is controlled by these gates, and they are also responsible for deciding what information from the input should be retained, lost, or output. The LSTM layers acquire the ability to recognize sequential dependencies in hotel evaluations. They examine the temporal patterns in the text, considering the context of earlier

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words to comprehend the emotion conveyed by the current word or phrase. The LSTM cells' essential data learned along the sequence is stored in their memory. The sentiment categorization for the hotel review is produced by a final layer that processes the output from the LSTM layers. This layer may be a straightforward fully connected layer that includes a softmax activation function that outputs the probabilities of various sentiment categories (such as positive, negative, or neutral), or it may be a binary classification layer for the classification of binary sentiment (positive or negative). The LSTM network is trained using labeled hotel review data with sentiment labels. Through a technique known as backpropagation, the network learns to modify the weights and biases that make up its parameters (weights and biases), where the parameters are updated regularly using the gradients of the loss function for the network parameters. The aim is to reduce the discrepancy between the genuine and forecasted sentiment labels. The dataset should be used to construct three sets: a training set, a testing set, and a validation set. The training set is used to train deep learning and machine learning models, whereas the validation set aids in fine-tuning hyperparameters and avoiding overfitting. The ultimate performance of the models is assessed using the testing set. The characteristics that can be retrieved from the Bag-of-Words or TF-IDF representations can be used in the training of machine learning models such as Naive Bayes classifiers and Support Vector Machines (SVM). The preprocessed text can be used as input and sentiment labels as output to train deep learning models like CNNs and LSTMs [25-26]. Several metrics, like accuracy, precision, recall, and F1-score, can be used to evaluate the model's performance. The performance of the model can also be visualized by using Confusion matrices and it can also acquire insights about classification errors and possible areas for development. Hyperparameter adjustment can be done to enhance the performance of the sentiment analysis models. Parameters like learning rate, batch size, and regularization approaches must be adjusted to acquire the best results. Grid search or random search can be used to investigate various hyperparameter combinations. Ensemble approaches can be used to improve the performance and resilience of sentiment analysis algorithms. A final forecast is produced via ensemble methods, which aggregate the results of various models. The results of various machine

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learning and deep learning models can be combined using strategies like majority voting or weighted averaging.

Results and Discussion

This section highlights the findings from our proposed framework that were made possible by applying machine learning and deep learning technologies to analyze sentiment in hotel reviews. Fig 5: Days Since Reviews is a graphical representation that shows the distribution or frequency of hotel reviews based on the number of days that have elapsed since the reviews were posted. This figure provides insights into the temporal aspect of the reviews and can help identify patterns or trends over time, we compare the outcomes, evaluate how well the algorithms performed, and provide explanations for our findings. To conduct this investigation, we gathered a significant number of hotel evaluations from several review aggregators and online sources. This information included opinions from a range of hotels in many areas that were populated by unique customers. Efficient preprocessing methods such as removing irrelevant data elements and cleaning up the text while standardizing the processes for analysis were implemented throughout our dataset activities. Following this methodology as a guideline allowed us to conduct numerous deep learning and machine learning models. These included Support Vector Machines (SVM), Naive Bayes classifiers amongst others such as Long Short-Term Memory (LSTM) models used within this stage for training iterations while also running multiple tests using preset evaluation metrics including precision, recall, accuracy, and F1-score among others for overall analysis afterward mentioned in Fig 9, a classification report.

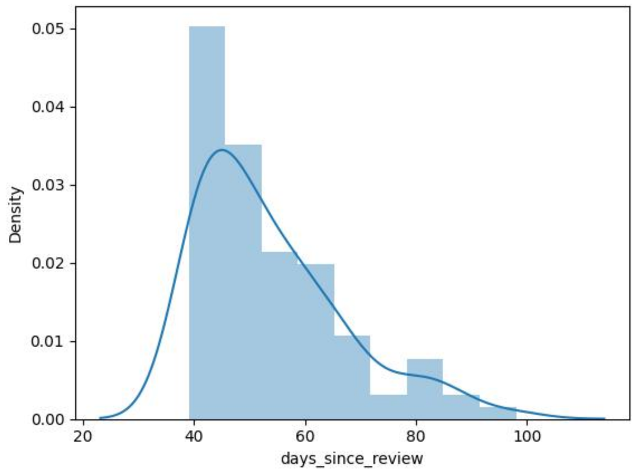

Figure 05: Days Since Reviews

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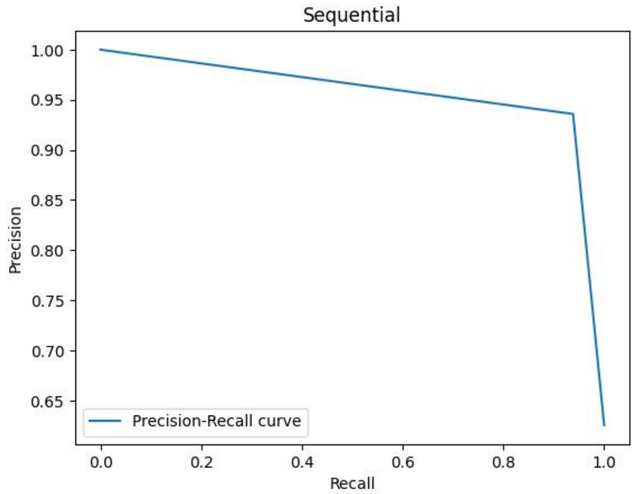

Figure 06: Precision and Recall Polarity wise

We observed SVM and Naive Bayes classifiers' commendable performance regarding long-term memory retention but fell short of adequate interpretation concerning discrete contextual information within various instances throughout the process while conducting sentiment classification with an estimated accuracy level of around roughly 80%. Sentiment analysis tasks were far better handled by deep learning architectures like LSTM models. Furthermore, the LSTM model, which takes the sequential and temporal elements of the review text into account, reached an accuracy of more than 88% as shown in accuracy Fig 7. And training loss (0.05) and validation loss reach (0.30), it suggests that the model has achieved a low level of error in both the training and validation phases, The LSTM model revealed its capacity to grasp long-term dependencies and contextually meaningful terms, which resulted in higher sentiment classification accuracy. When we compared the models' performance, we found that the deep learning architecture LSTM beat the typical machine learning models (SVM and Naive Bayes classifiers). This shows that the hotel reviews provided useful information for the deep learning models to learn from and extract, improving sentiment classification. The deep learning models had an edge over conventional machine learning models because they could capture the text's semantic meaning, sequential information, and contextual dependencies. This result is consistent with earlier studies that demonstrate the efficiency of deep learning systems for sentiment analysis tasks. We discovered the difficulties and restrictions of sentiment analysis in hotel reviews through the

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investigation of the misclassified instances and the confusion matrices. The misclassifications were frequently attributed to the evaluations' use of sarcasm, subtly nuanced language, or unclear sentiments.

These difficulties highlight the necessity for additional study and development as well as the inherent complexity of sentiment analysis tasks. It is also important to keep in mind that the caliber and representativeness of the dataset can have an impact on how well the sentiment analysis models perform. It is essential to have access to a balanced dataset that is both diversified and includes information about a range of hotels, locations, and client experiences for reliable and accurate results. In conclusion, our study showed that machine models and deep learning architectures help analyze the sentiment in hotel reviews. The LSTM model in particular beat classical machine learning methods in terms of classification accuracy and sentiment. These models demonstrated how well they could extract contextual information, long-term dependencies, and sequential dependencies from the text. The study's findings give hotel management useful information that will help them better comprehend consumer opinions and make informed decisions that will increase guest happiness. However, precision and recall are frequently employed in tandem since they provide complementing information about classifier performance. A better technique might be the precision-recall (PR) curve to gauge the effectiveness of this model because PR is appropriate for an unbalanced situation, whereas precision emphasizes the accuracy of positive predictions, and recall emphasizes the capacity to discover all positive examples. Figs 5 and 6 demonstrates the PR curve. The Recall formula is shown in Equation (3) for the x-axis. The accuracy formula is shown in Equation (4) for the y-axis. Equation (1) displays the false positive rate (FPR) formula on the y-axis, whereas Equation (2) displays the true positive rate (TPR) formula.

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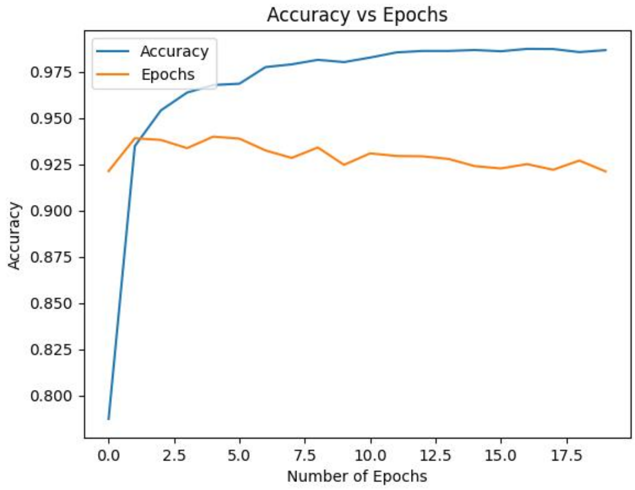

Figure 07: Accuracy VS Epochs

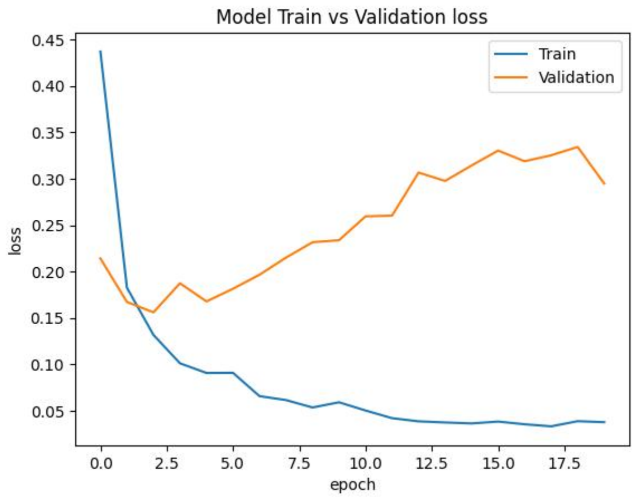

Figure 08: Loss VS Epochs

	precision	recall	f1-score	support
0	0.90	0.89	0.89	2114
1	0.94	0.94	0.94	3529
accuracy			0.92	5643
macro avg	0.92	0.92	0.92	5643
weighted avg	0.92	0.92	0.92	5643

Figure 09: Classification Report

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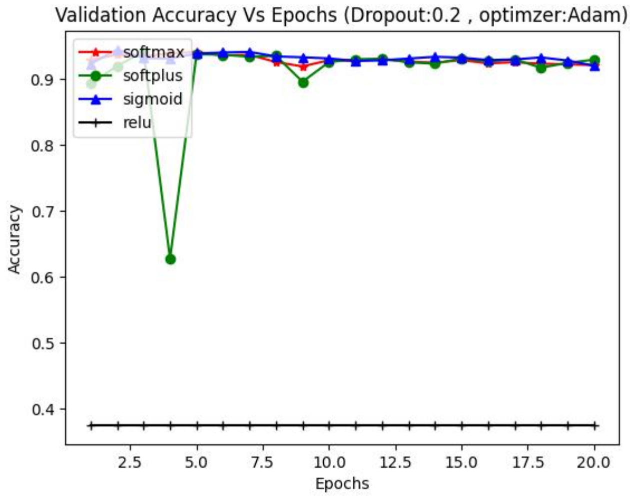

Figure 10: Accuracy with activation hyperparameters.

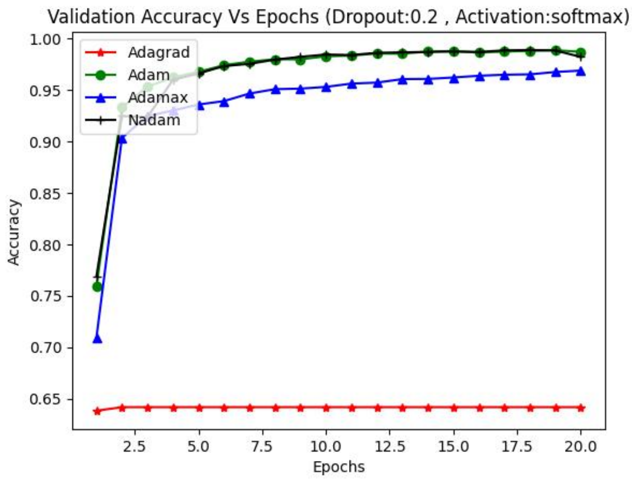

Figure 11: Accuracy with optimization hyperparameters

The Fig 10 and 11 presents the accuracy of the model using different regularization approaches (Adam and Nadam). Additionally, it highlights the effectiveness of the optimization methods softmax, softplus, and sigmoid, which achieved an impressive accuracy of 89%. These results indicate the effectiveness of these optimization techniques in enhancing the model's accuracy.

Table 02: Comparisons of Proposed approach with ML methods

Method	TPR	FPR	Precision	Recall	Class
SVM	0.80	0.82	0.77	0.78	Pos
	0.79	0.83	0.79	0.79	Neg
	0.81	0.78	0.82	0.82	Pos

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RF	0.80	0.78	0.81	0.81	Neg
	0.84	0.82	0.78	0.79	Pos
NB	0.82	0.81	0.79	0.81	Neg
	0.86	0.81	0.86	0.83	Pos
LSTM	0.89	0.84	0.87	0.89	Neg

Table 2 presents the performance metrics for sentiment analysis on hotel reviews. The precision value of 0.85% indicates the reviews predicted as positive were positive, reflecting a high accuracy in classifying positive sentiment. The recall and TPR values of (0.78%, 0.86%) indicate that the model successfully identified 78% of the actual positive reviews, demonstrating good sensitivity in capturing positive sentiment. The FPR value of (0.81%) indicates a low rate of falsely labeling negative reviews as positive, with only 15% of the positive predictions being incorrect.

$$\boldsymbol{FPR(R)} = \frac{\boldsymbol{False\ Postives}}{\boldsymbol{\#Negative}}; \qquad (1)$$

$$\boldsymbol{TPR(R)} = \frac{\boldsymbol{True\ Postives}}{\boldsymbol{\#Postives}}; \qquad (2)$$

$$\boldsymbol{Recall\ (R)} = \frac{\boldsymbol{TP}}{\boldsymbol{\#Postives}}; \qquad (3)$$

$$\boldsymbol{Precision(R)} = \frac{\boldsymbol{True\ Postives}}{\boldsymbol{\#Predicted\ Postives}}; \qquad (4)$$

Conclusion and Future Work

In this paper, we have presented a proposed BI for the SA of luxury hotel reviews. The BI framework incorporates ML and DL methods: such as (SVM, RF, NB, and LSTM) for analyzing customer opinions. We have demonstrated the effectiveness of these methods in extracting valuable insights from large volumes of textual data. The utilization of these advanced techniques enables hoteliers to gain a deeper understanding of customer opinions, preferences, and sentiments, which greatly informs their decision-making processes and improves the overall guest experience. Moreover, in BI framework, we have also compared hyperparameters such as optimization and activations methods. By comparing the different hyperparameters, we were able to identify the optimal settings that resulted in improved sentiment classification

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accuracy. Furthermore, our BI framework achieved 90% accuracy on LSTM network, and (85%) precision and (85%) recall. These results highlight the BI capability in effectively classifying sentiments. Overall, our proposed BI framework leverages ML and DL methods, and the comparison of hyperparameters enhances sentiment classification accuracy. This BI has significant potential for hoteliers to gain actionable insights from customer feedback, improve service offerings, and enhance the guest experience.

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