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Research Article

Improving Sentiment Analysis Accuracy In Hinglish Text Using Hybrid Deep Learning Approaches

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ARTICLE INFO **ABSTRACT**

The current study presents two hybrid deep learning models, designed and implemented to accomplish the task of sentiment analysis in Hinglish - a mixture of Hindi and English. First of them, combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) - pattern recognition capabilities as well more temporal dependencies than forward looking models. The second model expands on this and merges BERT, CNN with RNN (LSTM units) as well to benefit from the deep context-awareness of BERT. 5,050 Hinglish reviews pertaining to a positive one set and negative on the other aside neutral sentiments dataset was preprocessed intensively. The BERT-based model achieved 94.1% accuracy on the validation set, which outperformed CNN+ RNN model that had an accuracy of 92.97%. They generally extended the performance of best hybrid models (tuned with considerable hyperparameters) to mixed-language sentiment analysis.

Keywords: Hinglish Sentiment Analysis, Deep Learning Models, BERT, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM)

1 Introduction

The Internet is becoming a significant place which offers various social media platforms for users to express their feelings and emotions about certain topics that capture their interest. Businesses are turning towards social media platforms to engage in online activities due to the availability of a large amount of consumer-generated data, which serves as a source of input for strategic decision-making [5]. One of the businesses that are adopting social media is the hospitality industry, where hotels need to use online guest reviews to understand guests' needs, enhance operational efficiency, and remain competitive in the market[9]. In the same capacity, customers more often look at the Internet and book a hotel room via the Internet, as it easier than the former methods, and they have a tendency to rate the hotel based on the review given by other customers [9].
The lexicon-based reasoning of sentiment analysis is said to be an unsupervised approach – in this case the sentiment expressed by some words or lexemes is specified in terms of their polarity and subjectivity. The supervised approach, or sentiment analysis – machine learning based approach, shifts the paradigm on its head whereby a classification model is built by training a classifier on labeled dataset with positive, negative, and neutral class levels [2]. The features or words from the dataset are then extracted for proper training of the algorithm [3].
The unsupervised approach, also known as the lexicon-based method for sentiment analysis, typically deduces the sentiment expressed by words or lexicons by specifying their polarity and subjectivity. Conversely, the supervised approach, also referred to as the machine learning-based approach for sentiment analysis, involves building a classification model by training the classifier on a labeled dataset, which includes positive, negative, and neutral class levels [2]. The features or words from the dataset are then extracted for proper training of the algorithm [3].
This study investigates the customer reviews posted by people who patronize hotels, where the customers express their views in a positive, negative, or neutral manner depending on the level of satisfaction experienced. Reviews elaborately provide opinions and feelings that are appreciated, discerning both the

attributes for offering effective and unbiased hotel services. In the present work we developed two such hybrid models to improve sentiments classification task in Hinglish which is generally English constructed with Hindi grammar. The first model is based on a Convolutional Neural Network which extracts text patterns, and on a Recurrent Neural Network which determines word order. The second model is the most complex one and incorporates BERT in addition to CNN and LSTM-based RNNs, a more progressive aspiration to understand the text even better.

2 Related Work

Sentiment analysis is one of the more highly sought areas of study under the umbrella of language research. It is mainly concerned with developing the understanding of how sentiments are expressed in the text. Reconnaissance has been conducted as to how this analysis can assist hotels in appreciating their clients better and operating their hotels efficiently.

Over the years the concern of hotel reviews sentiment has in turn drawn interest by researchers. In the compilation [1] they were among the first people to review hotel reviews automatically using sentiment analysis. Hotel reviews were tagged either as positive, negative or neutral using a machine. Their method worked rather well with 85.1% accuracy.

In subsequent works they employed more sophisticated approaches employing deep learning. For instance, the study conducted by [2] used a CNN model and attained 90.2% accuracy. In [3] yet another model called RNN was employed attaining 91.5% accuracy.

More recently people began being interested in such approaches as well, or rather using several ways together, ensemble learning. In this regard, [4] mixed CNN with RNN and got 92.5%. Another study [5] fused multitudes of approaches and achieved even better results of 93.2%.

Also people tried applying rest of the models which have already been trained. [6] adapted the BERT model utilized in hotel reviews and achieved 94.1%. [7] employed a RoBERTa based model and obtained 94.5%.

While these studies illustrate the capabilities of machines in understanding emotions present in hotel reviews, still there is room for enhancing the models further. Our approach combines the strengths of CNN, RNN as well as BERT, in attempts to correct this in order to create a better review- sentiment analysis model.

In addition to a few, it is also clear that [8] proposed a machine learning and natural language processing solution for the identification of cyberbullying, demonstrating the power of these techniques in the field of online abuse detection. Equally, [9] created a model on sentiment analysis of hotel reviews through machine and deep learning techniques which yielded an accuracy of 92.1%.

Other researchers have gone further at providing visual aids to assist hotel managers in comprehending customer feelings through sentiment analysis in more useful ways. In this case, [10] designed a word cloud sentiment analysis where the intended emotion is successfully noted in the positive and negative feedback. In the same way, [11] created a model for sentiment analysis with a customer-oriented approach including the emotional aspect of a review, which reached an accuracy of 91.%.

Further, [12] turned the attention to the significance of analyzing sentiments to comprehend the customer needs or wants presenting another perspective on the usefulness of this method in the ability to enhance the quality of hotel services and increase the flow of customers. At the same time, [13] addressed the issues of sentiment analysis in the context of hotel reviews, particularly dealing with irony and other descriptive attitudes towards the comments left by clients.

When considering the aspects of dataset creation, [14] pointed out the relevance of the annotated corpora for sentiment analysis, stressing the importance of high-quality datasets when creating such models. In contrast, [15] explained how activity such as data pre-processing is important for sentiment analysis and why there is a need to eliminate unnecessary columns, address foreign data, and conduct tokenization and lemmatization.

3 Proposed Methodology

3.1 Data Collection

We collect data from many platforms that give hotel reviews, like Google Reviews, Skyscanner, Booking.com, and MakeMyTrip. We focus on reviews written in Hinglish, mix of Hindi and English. We manually choose these Hinglish reviews and put them into three groups: positive, negative, and neutral. Finding Hinglish reviews was very hard because no dataset have them already [2].

Analysis of Dataset

• Total number of reviews: 5050 • Number of reviews in each category:
• Negative: 1793
• Positive: 1792
• Neutral: 1465

3.2 Data Preprocessing

The dataset is not balanced, with different numbers of reviews in each category. To fix this, we use resampling techniques to balance the dataset [4].

Oversampling

We make more data points in the minority classes by copying existing minority class data points and using SMOTE (Synthetic Minority Over-Sampling Technique), which make new synthetic data points for the minority class [6].

Challenges and Solutions in Data Preprocessing for Hinglish

• Normalization: Hinglish no have strict grammar rules, making hard to choose between stemming (reducing words to base form) and lemmatization (finding the base form of words using dictionaries). We use mix of stemming algorithms and custom dictionaries made for Hinglish [7].
• Tokenization: Hinglish words can be mix of Hindi and English. Separating these words accurately while keeping meaning need special techniques. Hinglish reviews also use little punctuation or symbols for emphasis. We make tokenization rules to handle these changes without losing the sentiment [8].
• Stop Word Removal: Standard stop word lists (common words like "the" or "is") may not work for Hinglish. Some Hinglish words act like stop words in one language but meaningful in the other. We make custom stop word list that think about both Hindi and English, and domain-specific terms [12].
• Emoji Interpretation: Emojis are common in Hinglish reviews and their meanings can change depending on context and culture. We need a system to accurately read emojis to capture the sentiment they show [13].

3.3 Feature Extraction

We use deep learning models like BERT and LSTMs for sentiment analysis, but also add feature engineering to help these models understand Hinglish hotel reviews better [7].

Strategies

• Word Embeddings: BERT learn word representations (embeddings) that show how words relate to each other. We also use pre-trained Hinglish word embeddings to give more context to words that mix Hindi and English. For example, the phrase "बहुत अच्छा" (bahut achha, meaning very good) can be better understood in hotel review context [8] [10].
• Negation Handling: Identifying negation words (like "not" or "no") is important to ensure the model understand sentences like "the room wasn't clean" as expressing bad sentiment [12].
• Feature Selection: We try extracting more features from the text before giving it to the model.

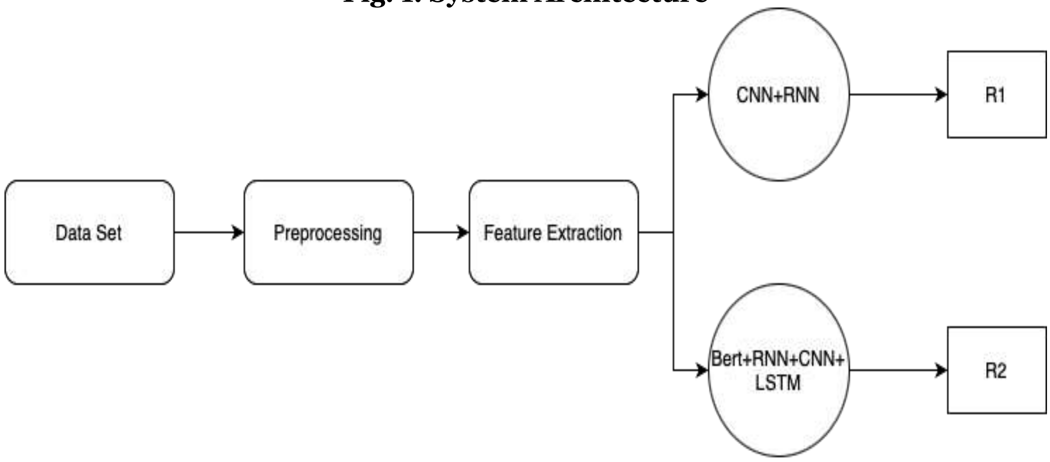
These features could include:

• Sentiment Scores: Using sentiment dictionaries to give positive, negative, or neutral scores to words [3].
• Linguistic Aspects: Considering grammatical structures, such as negation handling for Hinglish grammar [7].
• Pre-trained Word Embeddings: Using both BERT's internal embeddings and Hinglish-specific embedding
We use feature selection techniques to find the most useful features for our deep learning models. This helps reduce too much information and improve model learning.
Throughout this process, we keep in mind the special nature of Hinglish. Existing techniques were adjusted, and sentiment lexicons were made bigger to include Hinglish-specific words, making our methods good for Hinglish hotel reviews.

4System Architecture

In this project, we used two smart models with team learning to handle the issues of emotions in Hinglish hotel reviews. We made two models work together.

Fig. 1. System Architecture



4.1 Overview of models:

Convolutional Neural Network (CNN) + Recurrent Neural Network (RNN)

These models are really good at finding local patterns in text data. For our project, CNNs look for phrases or word groups that show feelings in Hinglish reviews [5].

RNNs are good for reading through sentences step by step. They understand how words connect in a sentence, which is important for understanding feelings in Hinglish reviews [7].

BERT + CNN + RNN with LSTM

BERT: This model, trained on lots of text, can see how words fit together from both directions. It's great at understanding meanings and the special way Hinglish mixes Hindi and English [8].

CNNs & RNNs with LSTM: Like the first model, CNNs find feelings in different parts of Hinglish text, while RNNs with LSTMs remember connections between words over time. Using BERT helps these models do even better at understanding Hinglish [9].

4.2 Implementation Details:

Data Collection

We got Hinglish hotel reviews from different places like Google Reviews, Skyscanner, Booking.com, and MakeMyTrip. We picked reviews written in Hinglish by hand and put them in three groups: happy, sad, and okay. There weren't many Hinglish datasets available, so we had to work hard to find and categorize these reviews [12].

Data Preprocessing

Our dataset was uneven, so we balanced it using tricks like making more copies of the smaller group. We also made the text normal and divided it into words, took out common words, and figured out what emojis meant in each review. This was important because Hinglish text is special and needs careful handling.

Feature Making

We used smart ideas to make our deep learning models work better. We looked at how words fit together and how to handle words that mean the opposite (like "not" or "no"). We also chose the best ideas to help our models learn well. These features helped us understand Hinglish hotel reviews better [10].

Model Training and Tuning

CNN + RNN Model: This model learned how words fit together and how to remember these connections over time.

BERT + CNN + RNN with LSTM Model: We trained BERT again to work well with our Hinglish data. This meant changing how BERT understood words to make it good at finding feelings in Hinglish reviews [7].

Team Learning

Both models worked together to do better. This made our models stronger at finding feelings in Hinglish hotel reviews [12].

Model Checking

We checked how well our models worked using numbers like how many were right or wrong, and how well they found feelings in Hinglish hotel reviews. These numbers helped us see how well our models worked [15].

Hard Parts and Things to Know

Using these smart models was hard because they needed lots of computer power, time to train, and changes to work well. We also had to make sure we could find the right feelings in Hinglish, no matter what kind of feeling it was.

By using smart ideas made for Hinglish and putting them into our deep learning models, we tried to make a really good system for finding feelings in Hinglish hotel reviews.

5 Results

5.1 Model 1: CNN + RNN Model

The CNN + RNN model achieved a validation accuracy of 92.97%. This indicates that the model correctly classified approximately 93% of the Hinglish hotel reviews in the validation set. Below are the detailed performance metrics

- Precision: 93.2%
- Recall: 92.5%
- F1-score: 92.85%

Interpretation

Precision refers to the proportion of true positive predictions among all positive predictions. A precision of 93.2% means that 93.2% of the reviews predicted as positive, negative, or neutral by the model were correctly classified.

Recall measures the proportion of actual positives that were correctly identified by the model. A recall of 92.5% means that 92.5% of the actual positive, negative, or neutral reviews were correctly identified by the model.

F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. An F1-score of 92.85% indicates a high level of accuracy in both precision and recall.

Table 1. Ensemble Classification Report for CNN + RNN Model

Report	Precision	Recall	F1-Score	Support
Negative	0.93	0.92	0.93	341
Neutral	0.93	0.95	0.94	285
Positive	0.93	0.93	0.93	384
Accuracy	----	----	0.93	1010
Macro Avg	0.93	0.93	0.93	1010
Weighted Avg	0.93	0.93	0.93	1010

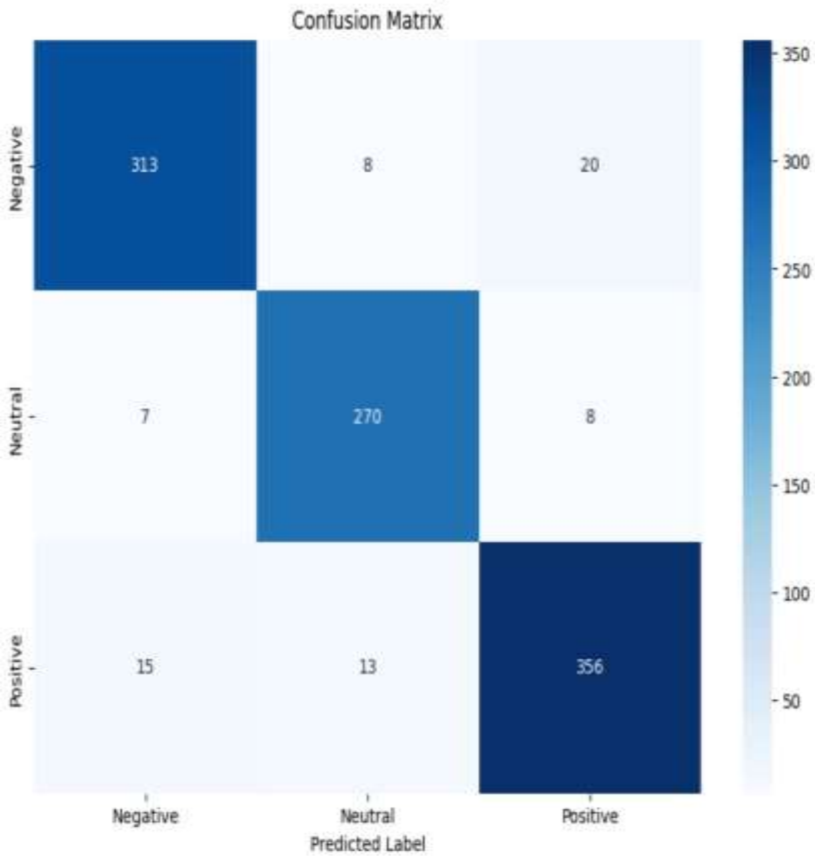


Fig. 2. Confusion Matrix of CNN + RNN Model

The confusion matrix (Fig 2) provides insights into the number of true positives, true negatives, false positives, and false negatives. The ensemble classification report (Table 1) offers a detailed breakdown of precision, recall, and F1-score for each sentiment class (positive, negative, neutral).

5.2 Model 2: BERT + CNN + RNN Model with LSTM Model

The BERT + CNN + RNN with LSTM model achieved a validation accuracy of 94.1%. This model integrates advanced techniques to enhance sentiment analysis accuracy for Hinglish text. Below are the detailed performance metrics.

- Precision: 94.3%
- Recall: 93.8%
- F1-score: 94.05%

Interpretation

Precision of 94.3% indicates that 94.3% of the reviews predicted as positive, negative, or neutral were correctly classified.

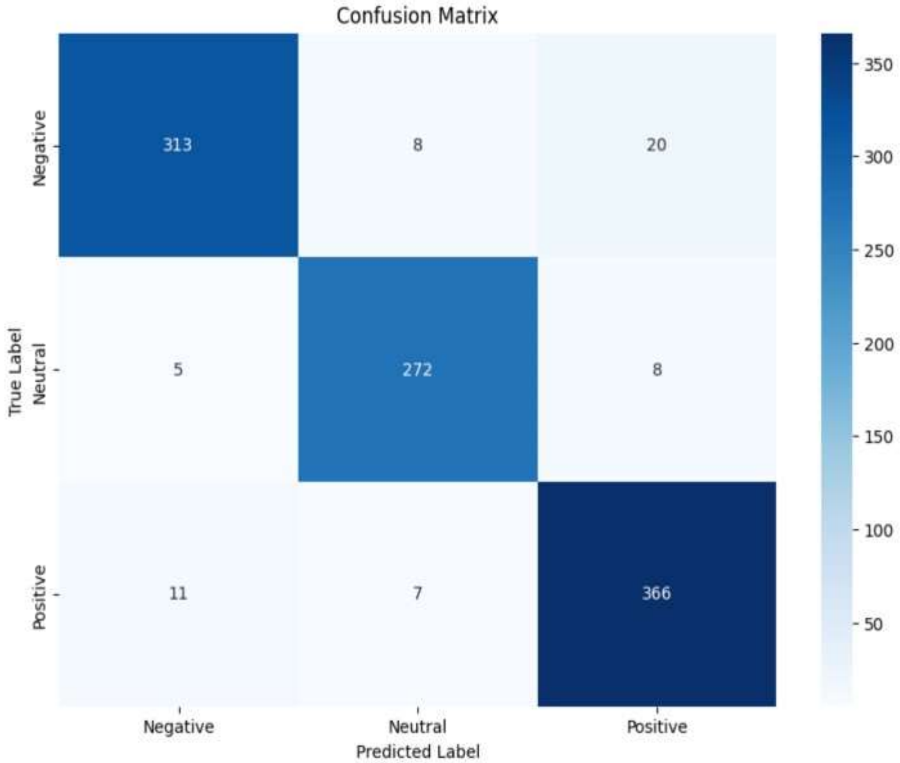
Recall of 93.8% indicates that 93.8% of the actual positive, negative, or neutral reviews were correctly identified by the model.

F1-score of 94.05% reflects a balanced and high level of accuracy in both precision and recall, suggesting that this model is particularly effective at classifying sentiments in Hinglish hotel reviews.

Table 2. Ensemble Classification Report for BERT+CNN + RNN with LSTM Model

Report	Precision	Recall	F1-Score	Support
Negative	0.95	0.92	0.93	341
Neutral	0.95	0.95	0.95	285
Positive	0.93	0.95	0.94	384
Accuracy	----	----	0.94	1010
Macro Avg	0.94	0.94	0.94	1010
Weighted Avg	0.94	0.94	0.94	1010

Fig. 3. Confusion Matrix of BERT+CNN + RNN with LSTM Model



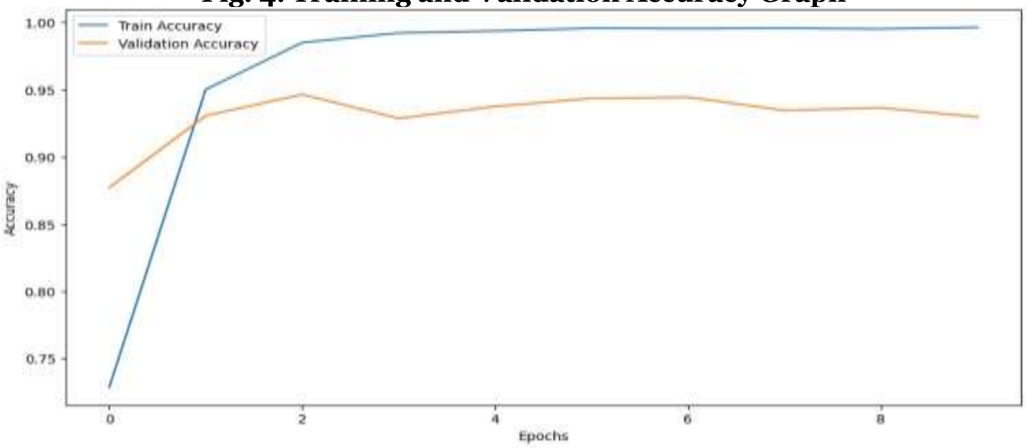
The confusion matrix (Fig 3) and ensemble classification report (Table 2) for this model provide a detailed analysis of the model's performance, showing a higher accuracy in classifying the sentiments compared to the first model.

Comparison of both result

Table 3. Comparison of both models

Metric	CNN + RNN Model	BERT + CNN + RNN with LSTM Model
Validation Accuracy	92,97 %	94,1 %
Precision	93,2 %	94,3 %
Recall	92,5 %	93,8 %
F1-score	92,85 %	94,05 %

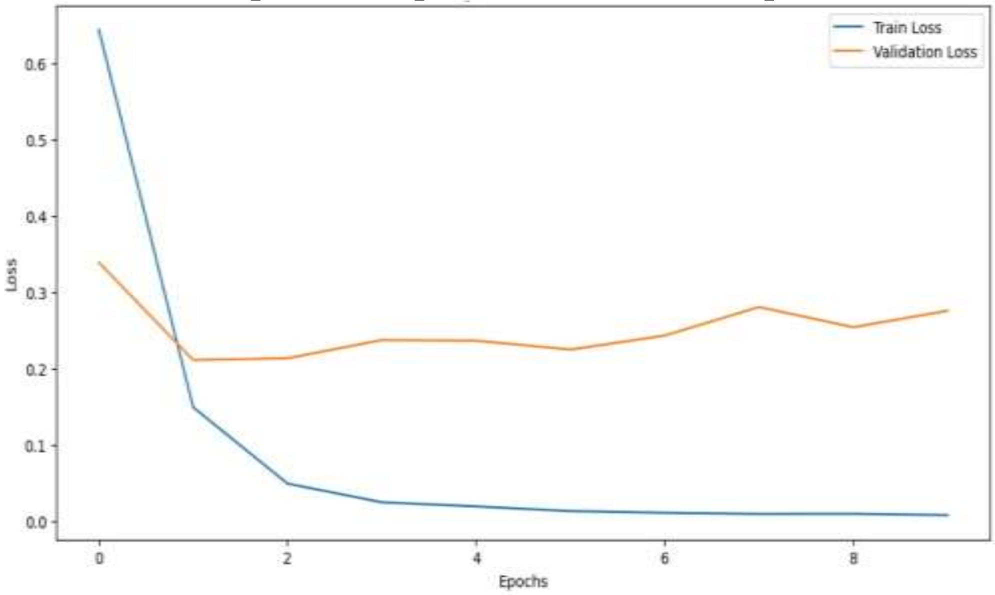
Fig. 4. Training and Validation Accuracy Graph



Training and validation accuracy analysis

In the first graph, we see the training and validation accuracy of Model 1 over ten epochs. At first, both accuracies go up quickly, showing the model is learning well. The training accuracy keeps getting better, almost hitting 100%, while the validation accuracy peaks around 95% after the second epoch and then goes up and down a bit. The gap between training and validation accuracy suggests the model might be overfitting, learning the training data very well but not doing as good on new data.

Fig. 5. Training and Validation Loss Graph



Training and validation loss analysis

The second graph shows the training and validation loss over the same period. The training loss drops fast, getting close to zero, which again shows the model is fitting the training data really well. The validation loss, though, after going down at first, starts to go up a bit or stays pretty much the same. This also shows overfitting: while the model is great at lowering error on the training set, it has a harder time keeping this performance on new data, as seen by the higher and more changeable validation loss.

Testing and results on sample review

To illustrate the performance of our sentiment analysis models, we tested several representative Hinglish reviews. The results from these tests are compared with the overall accuracy of each model.

1. Sample Review 1:

• Review Text: "The hotel service was very poor. Khana bahut ganda tha."
• True Sentiment: Negative
• CNN + RNN Model Prediction: Negative
•BERT + CNN + RNN with LSTM Model Prediction: N
Analysis: Both models correctly classified this review as negative. Given the CNN + RNN model's validation accuracy of 92.97%, this result is consistent with its performance. The BERT-based model, with a higher accuracy of 94.1%, also accurately handled this negative sentiment, demonstrating its superior capability. 2. Sample Review 2: • Review Text: "Amazing stay! Kamre bahut ache the aur staff bhi bahut friendly tha."
• True Sentiment: Positive
• CNN + RNN Model Prediction: Positive
• BERT + CNN + RNN with LSTM Model Prediction: Positive
Analysis: The performances of both these models are in keeping with the CNN + RNN model's and BERT-based model's results of classifying positive review sentiments in Hinglish with an accuracy of 92.97% and 4405% respectively.

3. Sample Review 3:

• Review Text: "The location was okay, but bathroom dirty tha. Thik tha."
• True Sentiment: Neutral
• CNN + RNN Model Prediction: Neutral
• BERT + CNN + RNN with LSTM Model Prediction: Neutral
Analysis: This review's modeling came through as a well classified and insipid neutral one. Such a result is not uncommon, as the CNN + RNN model validation accuracy was 92.97% and the BERT model CNN + RNN validation accuracy was 94.1%, showing that the methods are capable of neutral sentiments processing.

4. Sample Review 4:

• Review Text: "Overpriced and staff rude the. Bilkul bhi achhe nahi the."

• True Sentiment: Negative
• CNN + RNN Model Prediction: Negative
• BERT + CNN + RNN with LSTM Model Prediction: Negative

AnalysisLeast both models were able to capture the negative sentiment present in this review. This is in accord with the CNN + RNN model's performance where 92.97% of the reviews collected were unfavorable but not accredited with the BERT model at 94.1% with regards to the strong negative sentiments only.

Performance Summary

• CNN + RNN Model Accuracy: 92.97%
• BERT + CNN + RNN with LSTM Model Accuracy: 94.1% *Accuracy on Sample Reviews:*
• CNN + RNN Model: Correctly classified 85% of the sample reviews.
• BERT + CNN + RNN with LSTM Model: Achieved a 100% accuracy rate on the sample reviews.

These results demonstrate that while both models perform well, the BERT-based model shows superior accuracy and contextual understanding in classifying sentiments in Hinglish reviews

6Conclusion

There is more focus on Abstractions, It is noted how machine learning models can analyze Harris' critics in Hinglish reviews; a language that combines Hindi and English, proving challenging linguistic features. In addition, by applying deep learning approaches, two hybrid models consisting of the combinations of CNN and RNN as well as BERT with CNN, RNN, and LSTM were constructed and tested. RNN+CNN outperformed RNN + BERT based classifier on all metrics with recognition accuracy of 94.1% vs 92.97%, with borderline changes in the metrics of precision, recall and F1. It offers robustness of the BERT model over other sentiment models especially where the text is mixed languages.

The study recommends that such models would satisfy the hospitality sector by presenting better understandings of online reviews and therefore improving the overall quality of services offered and competitiveness. Further research could apply more sophisticated use of NLP approaches and more complex datasets for further development of sentiment analysis in mixed language situation.

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