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# Transformer Based Approaches for Sentiment Analysis on Restaurant Domain

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***Abstract: This project addresses the critical challenge of accurately analysing sentiment in restaurant reviews, where traditional machine learning methods struggle with linguistic nuances. Existing solutions, which are frequently basic ML or older deep learning models, typically lack the capacity to properly address class imbalance and capture deep contextual knowledge. To address these limitations, the study implements and evaluates two advanced transformer-based models: fine-tuning RoBERTa-large with Focal Loss, which focuses on learning from difficult examples and underrepresented classes, and a hybrid DistilBERT-CNN-BiLSTM model with fast gradient method, which combines efficient contextual embedding, local feature extraction, and sequential pattern recognition. These models aim to improve sentiment classification performance by making use of transformer-based architectures and modifying loss functions. Aspect-based sentiment analysis integration and the implementation of models for real-time feedback systems are examples of future development.***
***Keywords: Sentiment Analysis, Deep Learning, Transformers, Natural Language Processing (NLP), RoBERTa, DistilBERT, Hybrid Model, CNN (Convolutional Neural Network), BiLSTM (Bidirectional LSTM).***

## I. INTRODUCTION

Understanding consumer feedback, analysing social media trends, and forecasting the success of marketing campaigns are just a few of the many uses for sentiment analysis, the computational study of opinions and emotions in text [1]. In the digital age, customer feedback shared online, especially on review platforms, is invaluable for businesses. Timely and accurate evaluation of this feedback, such as that found in restaurant reviews, can significantly enhance business opportunities. Restaurant reviews, rich in subjective expressions, offer deep insights into dining experiences, covering aspects like food quality, service, and ambiance, thereby empowering both consumers and businesses.

However, the automated sentiment analysis of restaurant reviews faces notable challenges[20]. The language can be nuanced, featuring sarcasm, domain-specific jargon, and implicit sentiments. A common challenge in review datasets is class imbalance, characterized by the dominance of specific sentiment expressions (e.g., positive, negative, neutral), which can introduce bias into predictive models if not appropriately managed. While traditional machine learning methods have been used, they often require manual feature engineering and may fall short in capturing the deep contextual understanding needed for high accuracy. In contrast, deep learning models have shown superior performance by automatically extracting features and learning complex linguistic patterns, achieving higher accuracy with less manual intervention.

Recent advancements in Natural Language Processing, particularly transformer-based models like BERT, RoBERTa, and DistilBERT, offer powerful solutions through deep contextual learning and self-attention mechanisms. This study explores two such approaches: fine-tuning RoBERTa-large with Focal Loss to handle class imbalance and a hybrid DistilBERT-CNN-BiLSTM model using Weighted Cross-Entropy Loss for effective feature and sequence extraction. These models aim to enhance sentiment analysis accuracy and provide actionable insights for the hospitality industry.

*Approach 1*: RoBERTa (Robustly Optimized BERT Pretraining Approach): The project investigates fine-tuning RoBERTa (a robust Transformer model) using Focal Loss to handle imbalanced sentiment classes in restaurant reviews.

*Approach2*: Hybrid Model: A second approach combines DistilBERT (efficient embeddings), CNN (local features), and BiLSTM (sequential patterns) with fast gradient method for comprehensive analysis.

By implementing these two approachesfine-tuning RoBERTa with Focal Loss and developing a hybrid DistilBERT-CNN-BiLSTM model with fast gradient methodthe project aims to effectively address class imbalance and enhance sentiment classification in restaurant reviews.

*Approach 1*: *RoBERTa*: RoBERTa (Robustly Optimized BERT Pretraining Approach) is an advanced transformer-basedlanguage model developed to improve upon BERT by optimizing its training methodologyIt has been pre-trained on a large-scale corpus of text using a masked language modeling objective, whichenables it toacquire deep contextualized representations of language.

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Fine-tuning involves customizing a pre-trained model such as RoBERTa for a specific applicationsuch as sentiment analysisby further training it on task-specific labeled data to enhance its performance in that domain.This helps the model learn task-specific features without starting from scratch, making it more efficient and effective.

Focal Loss is a loss function that addresses class imbalance by reducing the impact of well-classified examples and focusing more on hard-to-classify or minority class samples. This helps prevent model bias toward the majority class and improves learning from under-represented sentiments.

In this project, RoBERTa is fine-tuned with Focal Loss to enhance sentiment classification by combining deep contextual understanding with effective handling of class imbalance, resulting in more accurate and balanced predictions.

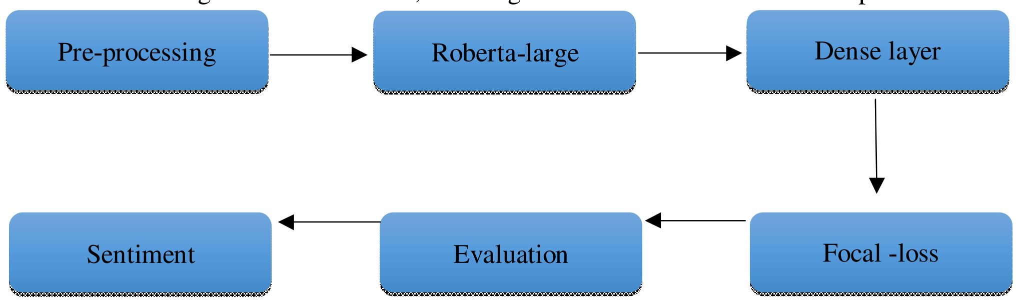


FIG. 1: FLOW CHART OF ROBERTA LARGE WITH FOCAL LOSS

*Approach 2: Hybrid Model***:**

DistilBERT (Distilled BERT) is a smaller, faster version of the BERT (Bidirectional Encoder Representations from Transformers) language model. It is created through a process called knowledge distillation, where a large model (BERT) teaches a smaller model (DistilBERT) to perform nearly as well while using fewer parameters and computing resources.

A Convolutional Neural Network (CNN) is commonly used in image processing but also works well for text classification. In NLP tasks, CNNs are used to detect local patterns, such as common phrases or combinations of words that strongly indicate sentiment.

BiLSTM is an extension of LSTM (Long Short-Term Memory), a type of Recurrent Neural Network (RNN) designed to handle sequential data and remember long-term dependencies. Bi-directional reads the input text in both directions at first the forward directionand then backward directionto understand the full context.

Focal Loss and Fast Gradient Method (FGM) are techniques used to improve model performance and robustness. Focal Loss mitigates class imbalance by emphasizing difficult-to-classify samples, whereas FGM boosts model generalization by applying adversarial perturbations to input embeddings during training.Combined, they help build more accurate and resilient models.In sentiment analysis, DistilBERT captures word context, CNN detects key phrases, and BiLSTM models sentence flow. Combined with focal loss and fast gradient method to handle class imbalance, this hybrid approach improves accuracy across all sentiment categories.

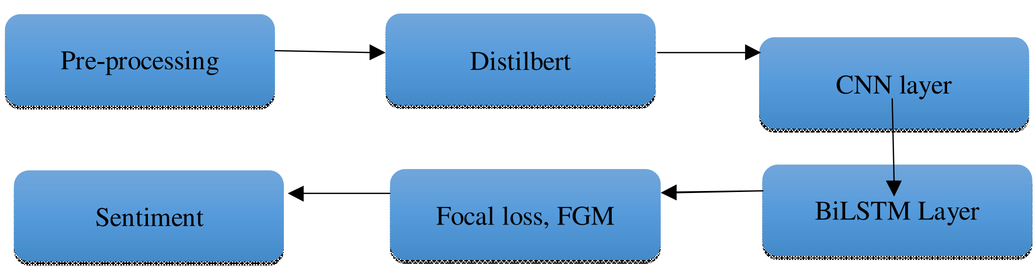


FIG. 3: FLOW CHART OF HYBRID MODEL WITH FAST GRADIENT METHOD

## II. LITERATURE REVIEW

Several papers [1, 2, 3, 5, 6] define the field of sentiment analysis as computationally defining and classifying opinions expressed in various online texts. This research often aims to understand customer attitudes towards products or services, as indicated by studies [2, 4, 6, 13], or to gauge public opinion on broader topics, a focus in other works [8, 10]. These analyses, as shown in various papers [2, 3, 4, 5, 6], frequently draw data from diverse online sources, with a notable emphasis in several studies on online restaurant reviews.

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Researchers, as indicated in papers [2, 4, 6] employ a range of methodologies including machine learning algorithms like Naive Bayes, SVM, and Random Forest, which demonstrated strong performance in contexts like restaurant review classification. Furthermore, other works [7, 8] explore more advanced deep learning techniques. Studies [3, 5, 18] utilize deep learning models like lstms, while papers [7, 18] also cover cnns, and research [19] focuses on Transformers, all increasingly applied to handle the large scale and unstructured nature of web data, as pointed out by papers [7, 8]. A significant sub-domain, explored in multiple papers [2, 3, 4, 5, 6, 12, 14, 17, 18], is Aspect-Based Sentiment Analysis (ABSA).

This area aims to identify sentiment towards specific features, an approach particularly evident in studies analyzing restaurant reviews [2, 3, 4, 5, 6], and is a core focus of general ABSA research [12, 14, 15, 17, 18]. Key challenges persist, as highlighted by research [7, 8, 19], including dealing with vast data volumes. The need for sufficient labeled data is addressed in papers [7, 14, 15, 17], while study [9] tackles the nuances of informal language and emojis, and papers [11, 18] discuss the difficulty in extracting context-dependent features.

Specific contributions from these studies are evident, where paper [4] presents frameworks for fine-grained sentiment classification, and study [3] introduces multi-dimensional evaluation models based on user reviews, particularly within the restaurant domain. Additionally, research [9] developed specialized lexicons for elements like emojis. Innovations further explored by these works include methods for combining textual information with sentiment diffusion patterns on social media, as detailed in paper [11]. Other papers address approaches for visual sentiment analysis [7, 16], and strategies to overcome data scarcity, such as weakly supervised learning detailed in paper [14], semi-supervised learning in paper [17], and cross-lingual learning discussed in papers [7, 15], with the latter often enhanced by contrastive learning [15].

Finally, comprehensive surveys, such as paper [12], map the issues and advancements within complex areas like ABSA, thereby guiding future research towards more accurate and robust sentiment understanding.

## III. WORK FLOW

The below is the flow chat represents the overall workflow of the proposed sentiment analysis system

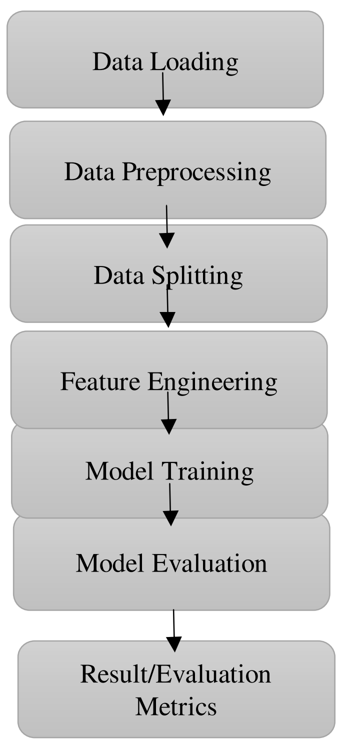


FIG. 4: WORKFLOW OF PROPOSED SENTIMENT ANALYSIS SYSTEM

The overall workflow of our proposed sentiment analysis system is illustrated in Figure 4. It begins with data loading and preprocessing, followed by feature extraction using transformer models.

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The core of the system investigates two distinct deep learning training approaches: first, fine-tuning RoBERTa-large with Focal Loss, and second, training a hybrid DistilBERT-CNN-BiLSTM model with fast gradient method. Both approaches incorporate techniques for handling class imbalance, with the latter also employing adversarial training.Finally, the performance of each model is evaluated, and comparative insights are produced.

## IV. METHODOLOGY

This section offers a thorough explanation of the methodology implemented during the study, going into detail on each step of the workflow's sentiment analysis procedure in figure 4. It starts with the preprocessing and data collection procedures, then move on to the feature engineering methods. The architectures of the two suggested deep learning models are then explained, as well as the training methods and performance evaluation criteria for each model.

### *1) Data Loading*

The dataset, consisting of restaurant names, reviewer identities, reviews, and associated ratings, is loaded from Excel or CSV files. Non-numeric or missing values are filtered to ensure clean and structured input data.

TABLE 1:SAMPLE DATASET

| S.No | Restaurant | Reviewer | Review | Rating |
|---|---|---|---|---|
| 1 | Royal Spicy Restaurant | Venkateshkumar | Good | 5 |
| 2 | Royal Spicy Restaurant | Karishma Shaik | good | 5 |
| 3 | Royal Spicy Restaurant | Murali Murali | Nice,great | 5 |
| 4 | Royal Spicy Restaurant | Manu Chowdary | Worst packing | 1 |
| 5 | Royal Spicy Restaurant | AT Veerareddy | good service keeps it up | 5 |
| 6 | Royal Spicy Restaurant | Sainaveen | simply superb... | 5 |
| 7 | Royal Spicy Restaurant | Ravi Gowthu | excellent. ordered for 3rd time. | 5 |
| 8 | Royal Spicy Restaurant | Susanta Sutar | okay | 3 |
| 9 | Royal Spicy Restaurant | Sharath | superb | 5 |
| 10 | Royal Spicy Restaurant | Gnana Prasuna | nice delivery | 5 |

### *2) Data Preprocessing*

Each review is mapped to a sentiment label based on its rating: scores 1–2 is*Negative*, 3 is *Neutral*, and 4–5 is*Positive*. The textual content is cleaned and tokenized using the appropriate tokenizer: RoBERTa for the first approach and DistilBERT for the second. Both models are configured to handle a maximum input length of 128 tokens, with padding and truncation applied to ensure uniformity.

### *3) Data Splitting*

The data is split into training and validation sets using stratified sampling (80:20 ratio), maintaining equal class distribution to support balanced model training and evaluation.

### *4) Feature Engineering*

Approach 1: RoBERTa-large + Focal Loss: In this approach, the RoBERTa-large model is employed as the backbone for extracting deep semantic representations of the input text. RoBERTa, a robustly optimized version of BERT, processes the tokenized input using multiple transformer layers to generate contextualized embeddings for each token. The [CLS] token representation (or the pooled output) is extracted as a summary of the entire input sequence. This vector is then passed through a fully connected dense layer that maps the high-dimensional embedding to the sentiment classification output space. This architecture allows the model to leverage RoBERTa's pre-trained language understanding, focusing on context-sensitive interpretations of the review text. No manual feature extraction is required, as RoBERTa inherently captures syntactic and semantic nuances within the input.
Approach 2: Hybrid DistilBERT + CNN + BiLSTM + Focal Loss. In this hybrid model, DistilBERTa lightweight and faster version of BERTis used as the initial embedding generator. DistilBERT produces contextualized embeddings from input sequences with reduced computational overhead while maintaining high accuracy.

These embeddings are passed to a 1D Convolutional Neural Network (CNN) layer, which acts as a local feature detector, extracting n-gram level patterns from the token sequence. The CNN output is then fed into a Bidirectional Long Short-Term Memory (BiLSTM) layer, which captures forward and backward temporal dependencies within the sequence. The combined CNN-BiLSTM architecture enables the model to learn both local semantic structures and long-range dependencies. The BiLSTM output is aggregated using mean pooling across the sequence, followed by dropout regularization and a dense classification layer for the final sentiment prediction.

*5) Model Training*

*Approach 1:*RoBERTa-large + Focal Loss + FGM:The RoBERTa-based model is fine-tuned on the sentiment classification task using Focal Loss as the objective function. Focal Loss addresses the problem of class imbalance by down-weighting well-classified examples, thus focusing the learning process on hard and minority-class samples like Neutral sentiments. During training, Fast Gradient Method (FGM) is used as an adversarial training technique. FGM perturbs the word embeddings slightly in the direction of the loss gradient, forcing the model to learn robust patterns that generalize better to unseen and adversarial inputs. The optimization is handled by the AdamW optimizer, which is well-suited for transformer models, combined with a learning rate scheduler that linearly warms up and then decays the learning rate to stabilize the training process. Gradient clipping is applied to prevent exploding gradients, especially in deeper models like RoBERTa.

*Approach 2:* Hybrid DistilBERT + CNN + BiLSTM + Focal Loss + FGM: The hybrid architecture is also trained using Focal Loss, with class-specific alpha values tailored to the distribution of *Negative*, *Neutral*, and *Positive* samples. The Focal Loss helps emphasize misclassified or underrepresented examples during learning. Just like in the RoBERTa model, FGM is applied, but it specifically targets the embedding layer within the DistilBERT component of the hybrid architecture. This perturbation regularizes the model by exposing it to adversarial examples during training, enhancing resilience. Due to the presence of custom layers like CNN and BiLSTM, the training benefits from both pre-trained representations and task-specific feature learning. The model is optimized using AdamW, and training stability is maintained using learning rate scheduling with a warm-up phase. The combined structure allows the model to efficiently learn from context, local dependencies, and sequential patterns while being more computationally efficient than RoBERTa.

*6) Model Evaluation*

Model performance is tracked across epochs using metrics like training or validation loss, accuracy, and per classclassification scores. The best-performing models, based on validation accuracy, are saved for inference.

*7) Result / Evaluation Metrics*

Both models are evaluated on the validation dataset using precision, recall, F1-score, and accuracy. Additional inference is conducted on unseen examples to visually verify sentiment predictions. While RoBERTa demonstrates superior contextual understanding, the hybrid DistilBERT model offers competitive performance with significantly reduced computational cost.

## V. RESULTS

This section shows the results obtained from the sentiment classification task on restaurant reviews using two deep learning approaches. The dataset contained 9,955 reviews after cleaning, categorized into three sentiment classes: Negative (2,447), Neutral (1,239), and Positive (6,268). In the first approachRoBERTa-base model with Focal Lossreached a peak validation accuracy of 0.8794, handling class imbalance effectively. Similarly, second approach hybrid model combining DistilBERT embeddings with CNN and BiLSTM layers also achieved a best validation accuracy of 0.8594 at epoch 4. Both models demonstrated consistent improvements across training epochs, with high F1-scores for the Positive and Negative classes and relatively lower scores for the Neutral class. Inference examples further illustrate the models' predictions, including cases with varying confidence levels.

### *A. Training & Validation Metrics (Per Epoch)*

These metrics are reported during each training cycle (called an **epoch**) to monitor the model’s learning progress.

*1)* Epoch: An epoch is defined as a single complete cycle through the entire training dataset while training a model.
*2)* Train Accuracy: How well the model predicts the training data (i.e., % of correct predictions on training set).
*3)* Validation Accuracy: How well the model generalizes to unseen data (i.e., % of correct predictions on validation set). A more important metric than train accuracy.

4) Train Loss: Train Loss represents how accurately the model is performing on the training data by quantifying the error during learning. Lower is better. It's based on the model's confidence and correctness.
5) Val Loss :Same as train loss, but on validation data. It helps to detect overfitting: if val loss increases while train loss decreases, your model may not generalize well.

TABLE 2: ROBERTA MODEL TRAINING & VALIDATION METRICS

| Epoch | Train Accuracy | Validation Accuracy | Train Loss | Val Loss |
|---|---|---|---|---|
| 1 | 0.7770 | 0.8644 | 0.0672 | 0.0437 |
| 2 | 0.8701 | 0.8754 | 0.0377 | 0.0392 |
| 3 | 0.9052 | 0.8754 | 0.0274 | 0.0470 |
| 4 | 0.9376 | 0.8744 | 0.0191 | 0.0508 |

TABLE 3: HYBRID MODEL TRAINING & VALIDATION METRICS

| Epoch | Train Accuracy | Validation Accuracy | Train Loss | Val Loss |
|---|---|---|---|---|
| 1 | 0.7619 | 0.8493 | 0.0791 | 0.0530 |
| 2 | 0.8639 | 0.8518 | 0.0472 | 0.0476 |
| 3 | 0.8812 | 0.8513 | 0.0400 | 0.0440 |
| 4 | 0.8975 | 0.8594 | 0.0353 | 0.0425 |

### *B. Final Classification Report – Best Model (Epoch 3)*

This section presents the evaluation outcomes of the best-performing models from both training approaches: the BaselineDistilBERT model and the Hybrid DistilBERT + CNN + BiLSTM model. The results highlight their ability to classify restaurant review sentiments across three classes: Positive, Negative, and Neutral.

#### *1) Per class Metrics*

Per-class metrics include precision, recall, F1-score, and support for each sentiment category (Negative, Neutral, Positive).

- Precision indicates the proportion of correctly predicted instances out of all predictions made for a given class.
- Recall indicates the proportion of actual instances of a specific class that the model successfully identified, reflecting its effectiveness in capturing that class.
- The F1-score represents the harmonic mean of precision and recall, offering a balanced metric to evaluate a model's performance for each class.
- Support denotes the number of actual instances for each class in the validation set.

TABLE 4: ROBERTA MODEL PER CLASS METRICS

| Sentiment | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Negative | 0.88 | 0.88 | 0.88 | 489 |
| Neutral | 0.53 | 0.55 | 0.54 | 248 |
| Positive | 0.94 | 0.94 | 0.94 | 1254 |

TABLE 5: HYBRID MODEL PER CLASS METRICS

| Sentiment | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Negative | 0.86 | 0.88 | 0.87 | 489 |
| Neutral | 0.48 | 0.52 | 0.50 | 248 |
| Positive | 0.94 | 0.92 | 0.93 | 1254 |

### 2) *Overall Metrics*

It summarizes the model's performance across all classes:

- Accuracy represents the percentage of total correct predictions over all validation samples.
- Macro Average F1-score computes the unweighted mean of F1-scores across all classes, treating each class equally regardless of support.
- Weighted F1-score accounts for both the F1-score and the number of instances per class, giving a more balanced view of performance on imbalanced datasets.

TABLE 6: ROBERTA MODEL OVERALL METRIC

| Metric | Value |
|---|---|
| Accuracy | 0.87 |
| Macro Avg F1 | 0.79 |
| Weighted F1 | 0.88 |

TABLE 7: HYBRID MODEL OVERALL METRIC

| Metric | Value |
|---|---|
| Accuracy | 0.8594 |
| Macro Avg F1 | 0.77 |
| Weighted F1 | 0.86 |

### 3) *Graphs*

Training and validation loss/accuracy curves track the learning behavior of the model over each epoch.

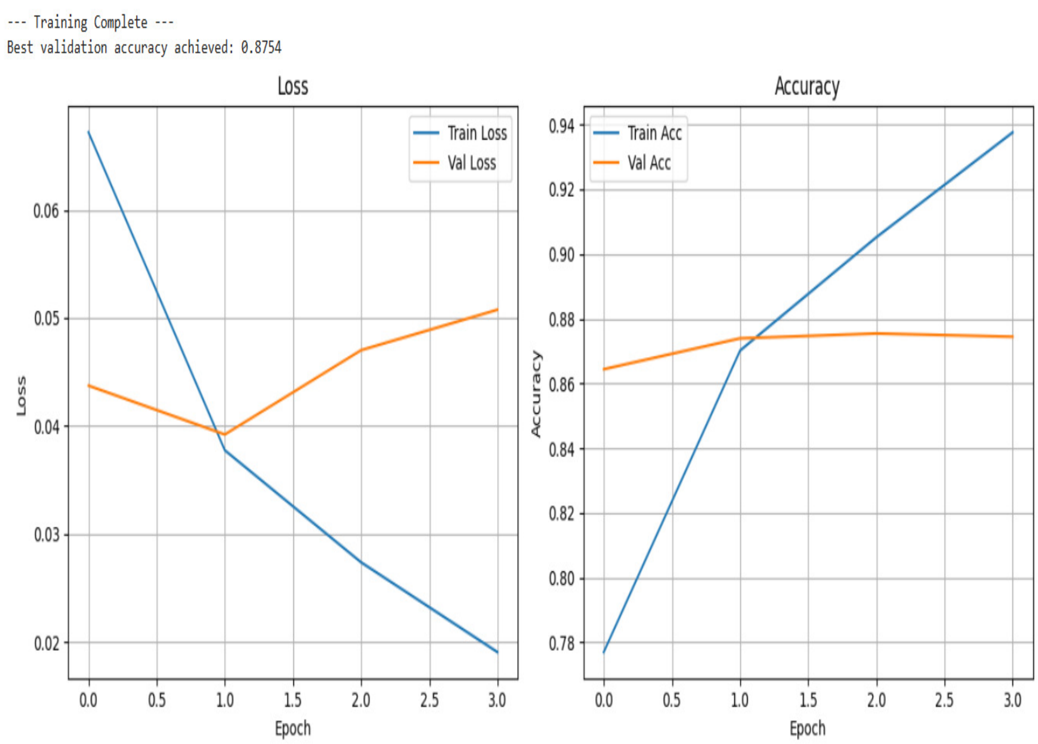


FIG. 5: ROBERTA MODEL TRAINING AND VALIDATION LOSS GRAPH

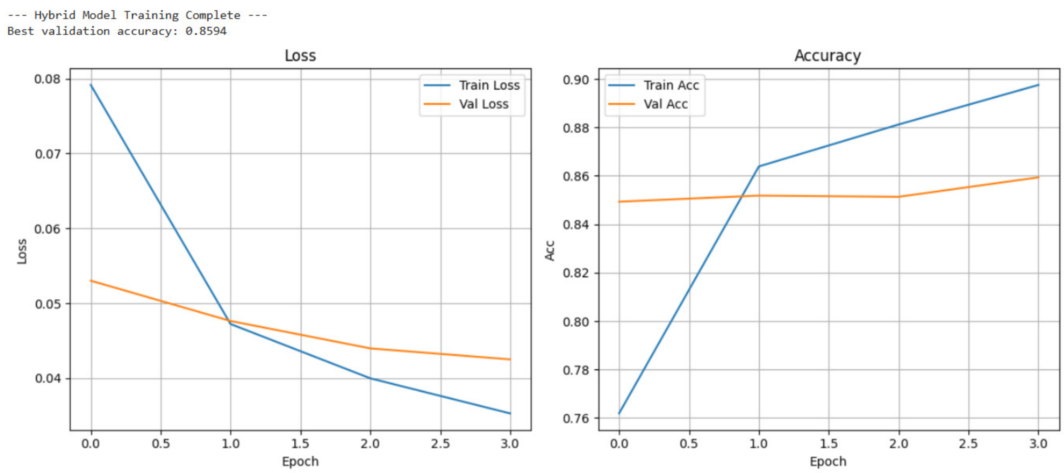


FIG. 6: HYBRID MODEL TRAINING AND VALIDATION LOSS GRAPH

### C. Inference Examples

Below is sample inference results on the validation set.

TABLE 8: INFERENCE EXAMPLES

| Restaurant | Reviewer | Review | Actual Sentiment | Predicted Sentiment | Confidence |
|---|---|---|---|---|---|
| Tandoori Food Works | Gnaneswar Seshu | "I don't like spicy food but after eating biryani here I feel like it would be good if it is spicy..." | Negative (0) | Positive | 0.5284 |
| Urban Asia - Kitchen & Bar | Tinni Ghosh | "I went to Urban Asia on a date... Sushi was not available at all. We were heartbroken..." | Negative (0) | Negative | 0.6661 |
| Club Rogue | Varsha Ane Nenu | "The manager was unprofessional and asked us to leave... called bouncers upon us... The reception is bad..." | Negative (0) | Negative | 0.8627 |

## VI. CONCLUSION

This work successfully addressed the important issues of linguistic nuance and class imbalance in restaurant review sentiment analysis. The project achieved high validation accuracies (0.8754 and 0.8594, respectively) and robust F1-scores by implementing and evaluating two sophisticated transformer-based approaches: a hybrid DistilBERT-CNN-BiLSTM architecture and a fine-tuned RoBERTa-large model, both of which were enhanced with specialized loss functions (Focal Loss) and adversarial training. This is a significant advance over traditional machine learning and simpler deep learning algorithms, which frequently fail under such complications. The created models show a better ability to acquire profound contextual awareness and efficiently address data imbalance, especially when it comes to categorizing positive and negative attitudes.

Future research could focus on integrating aspect-based sentiment analysis to provide more nuanced insights and enhancing algorithms for more accurate neutral class classification.Additionally, investigating the potential of even larger language models (LLMs) offers a viable path forward.

Without much fine-tuning, LLMs may be able to provide even more accuracy and more nuanced sentiment interpretations due to their improved comprehension of complicated linguistic structures, sarcasm, and subtle contexts.

These approaches have a high potential for practical application in the hotel industry, as they enable automated client feedback analysis, improve service quality, and enhance strategic decision-making via dependable, real-time sentiment monitoring systems. This conclusion is well supported by the empirical facts and comparative analysis offered in this study.

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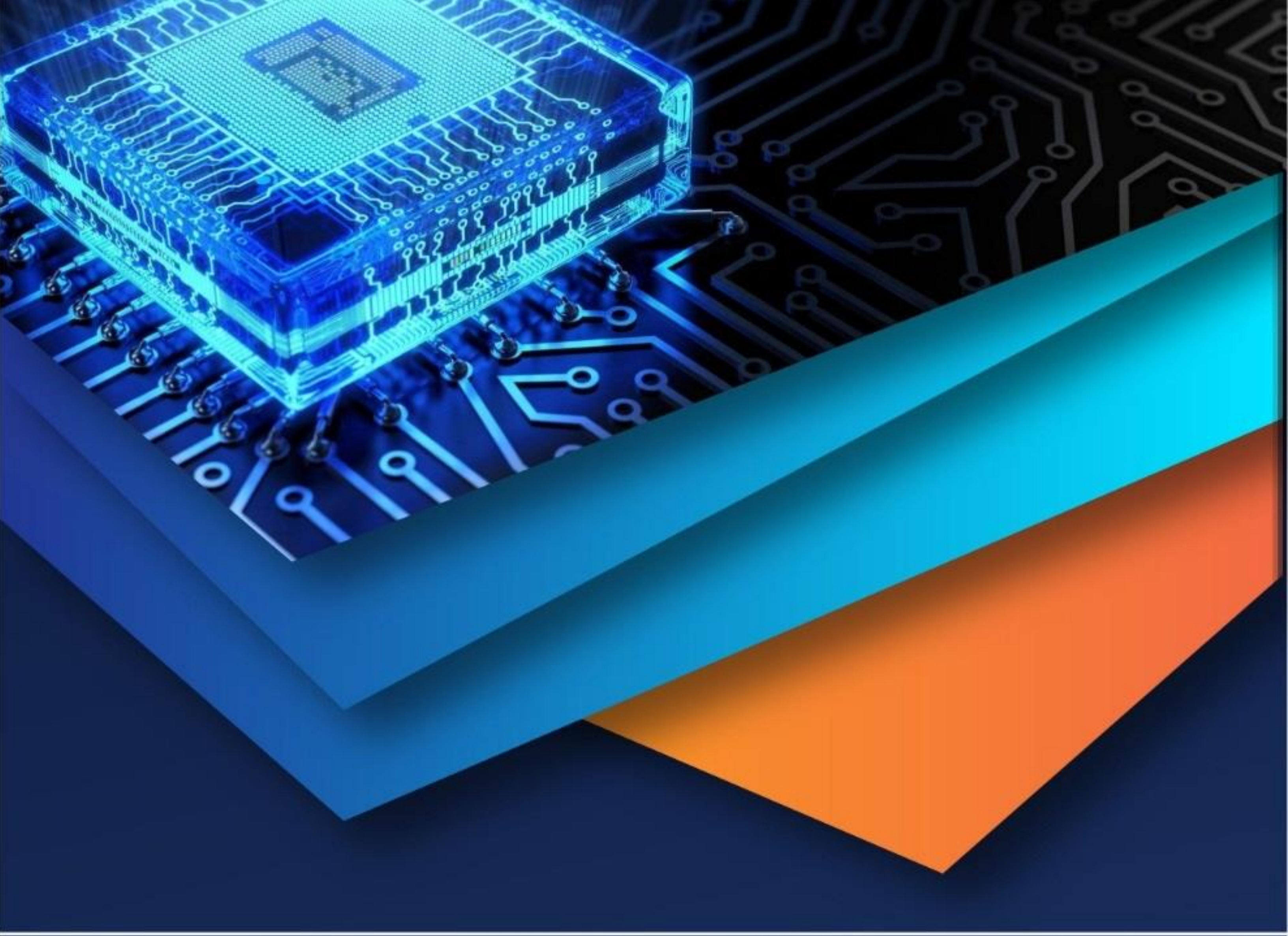


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