Automated Response Generation for Negative College Reviews using Sentiment Analysis

A PROJECT REPORT
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ABSTRACT

Online reviews have become an important medium for students to express their opinions about colleges, directly influencing institutional reputation and accreditation outcomes. While traditional sentiment analysis methods classify reviews as positive, negative, or neutral, they often fail to capture deeper insights such as specific aspects of feedback (placements, faculty, infrastructure, hostel facilities) or provide meaningful responses to student concerns.

This project proposes a multilingual, aspect-based sentiment analysis framework with automated response generation. Reviews are collected from multiple platforms and processed using text cleaning, tokenization, stopword removal, and translation. Baseline machine learning models such as Naïve Bayes and **SVM** are compared with advanced deep learning models like **CNN** and **LSTM**, while transformer-based models such as **BERT** and **IndicBERT** are employed for high accuracy in multilingual contexts.

A unique feature of this system is its ability to generate polite, professional, and context-aware automated responses for negative reviews, thereby reducing the communication gap between students and institutions. To ensure transparency and trust, Explainable AI (XAI) techniques are integrated to highlight the reasoning behind sentiment classifications.

The expected outcomes include a curated multilingual dataset, a high-performance sentiment classification model, an automated response framework, and an interactive dashboard for institutional insights. This work aims to enhance communication, improve quality in higher education, and support accreditation processes such as **NAAC/NIRF**.

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INTRODUCTION

In recent years, the digital landscape has transformed the way individuals and organizations communicate and interact. For educational institutions, online platforms such as college websites, social media, and review portals have become major channels through which students and stakeholders express their opinions and experiences. These reviews play a significant role in influencing the perception and reputation of colleges among prospective students and their families. While positive reviews serve as a valuable tool for building credibility, negative reviews can have a detrimental effect, discouraging admissions and damaging the institution's image if not handled appropriately.

Traditionally, addressing online reviews has been a manual process carried out by administrators or placement officers. However, this approach comes with several challenges. The growing volume of online feedback makes it difficult to monitor and respond in a timely manner. Inconsistencies in tone and professionalism, coupled with delays in communication, often lead to student dissatisfaction. In many cases, negative reviews remain unanswered, creating a perception of negligence or lack of concern from the institution's side. These challenges highlight the urgent need for an automated, intelligent system that can respond effectively to negative reviews and help institutions maintain transparency and trust.

This research project aims to develop an automated response generation system for negative college reviews by leveraging the power of Natural Language Processing (NLP), Sentiment Analysis, and Machine Learning. The system will first analyze incoming reviews to determine their sentiment and filter out the negative ones. Further, it will employ aspect-based sentiment analysis (ABSA) to identify specific areas of concern such as faculty quality, infrastructure, placements, administration, or student support services. Based on the identified aspects, the system will then generate an appropriate response that is not only context-aware but also empathetic and professional in tone.

By automating the response process, the proposed system reduces dependency on manual monitoring and ensures that reviews are addressed promptly and consistently. This, in turn, will enhance student engagement, improve satisfaction, and strengthen the overall reputation of the institution. Beyond addressing grievances, the system also provides valuable insights into recurring issues raised by students, allowing administrators to make data-driven improvements in academic and non-academic areas.

Furthermore, the scope of this research extends beyond educational institutions. The framework developed can be adapted to various domains where online reviews significantly influence decision-making, such as healthcare, hospitality, and e-commerce. Thus, this project not only addresses a pressing issue in the academic sector but also contributes to the broader field of automated review management and response generation.

In conclusion, the research introduces a novel, technology-driven approach to handling negative reviews through automation. By integrating sentiment analysis with automated response generation, the project ensures timely, empathetic, and consistent communication with stakeholders, thereby protecting and enhancing the digital reputation of colleges in an increasingly competitive environment.

LITERATURE REVIEW

1. Early Approaches: Lexicon and Traditional Machine Learning

One of the earliest works, *Borade et al. (2017)*, applied **Naïve Bayes** and decision list classifiers with **bag-of-words** and **bigrams** features. Their study on college reviews extracted positive or negative sentiments, providing insights into user requirements, improvement suggestions, and experiences. Although effective for small datasets, these models suffered from limitations in handling **sarcasm, context, and domain-specific terms**, often resulting in modest accuracy levels (~70–80%).

Similarly, *Dsouza et al. (2019)* conducted a comparative study using **Support Vector Machines (SVM)**, **Multinomial Naïve Bayes**, and **Random Forests** on student feedback collected via Google Forms. Their findings indicated that **Naïve Bayes** achieved higher accuracy (~85–88%) than SVM or Random Forest in smaller datasets, while SVM performed better with larger corpora. However, the study only focused on overall polarity (positive/negative/neutral) and lacked **aspect-based analysis**.

These early methods highlighted the **simplicity, low computational cost, and interpretability** of classical ML algorithms but also exposed their inability to capture deeper semantics or long-range dependencies in textual data.

2. Expansion to Social Media Data

As social media platforms became a primary source of student opinions, *Katkar et al. (2020)* proposed sentiment analysis on **Twitter and Facebook data** to assess colleges in Pune. Using **Naïve Bayes and SVM**, they classified reviews into positive and negative categories, achieving ~80–85% accuracy, with **SVM outperforming Naïve Bayes**. Their system also integrated geospatial analysis to suggest the shortest routes to top colleges, making it a practical application. However, the study struggled with the **noisy and unstructured nature of social media language**, which reduced precision.

3. Hybrid and Comparative Models

Chandurkar & Tijare (2021) provided a comparative review of sentiment analysis on colleges, exploring ML methods such as **SVM, Maximum Entropy (MaxEnt), and Naïve Bayes**, alongside emerging deep learning approaches. Their findings suggested that **MaxEnt achieved up to 96% accuracy** in some contexts, outperforming other classifiers. However, they also noted that deep learning methods struggled with **long-range dependencies** and required **large labeled datasets**. The study emphasized the necessity of combining multiple techniques (hybrid approaches) and leveraging parallel processing for efficient real-time analysis.

4. Aspect-Based Sentiment Analysis (ABSA)

A key advancement in educational sentiment analysis is the move from **document-level polarity classification** to **aspect-based sentiment analysis (ABSA)**.

- *Jazuli et al. (2023)* implemented ABSA on Indonesian student reviews using **Indo-BERT** and compared it with traditional classifiers (Naïve Bayes, KNN, Decision Trees). With a dataset of **10,000 reviews**, their Indo-BERT model achieved **~88–89% accuracy** in sentiment classification and **0.897 F1-score** in aspect extraction. This approach enabled fine-grained analysis of sentiments towards aspects like **lecturers, curriculum, infrastructure, and services**, offering universities actionable insights. Despite strong performance, the method was constrained by **language dependency** (specific to Indonesian) and **manual aspect labeling inconsistencies**.
- In a similar direction, *Gullipalli & Dholey (2024)* applied a **fine-tuned BERT model** to analyze Indian college reviews. Their model achieved **91% accuracy**, outperforming earlier approaches. Unlike traditional methods, their system classified reviews into multiple categories such as **placements, campus life, academics, research collaboration, outreach programs, and examination patterns**, providing a more **nuanced understanding** of student concerns. The study highlighted the **effectiveness of BERT's contextual embeddings**, but also pointed out challenges like **computational expense** and **cultural/linguistic variations** in Indian student reviews.

These works demonstrate that **transformer-based ABSA models** provide superior performance, context understanding, and actionable insights compared to earlier lexicon or ML-based methods.

5. Systematic Reviews and Mapping Studies

A broader view of the research landscape was offered by *Kastrati et al. (2021)*, who conducted a **systematic mapping review** of 92 primary studies published between 2015–2020. Their review classified approaches into **lexicon-based, ML-based, and DL-based techniques**, noting a shift towards **deep learning models** in recent years. They highlighted critical challenges:

- Lack of **standardized and structured datasets** for educational sentiment analysis,
- Limited focus on **emotion detection** beyond simple polarity,
- Insufficient **cross-lingual and cross-cultural adaptability**,
- Need for **aspect-level classification** instead of document-level.

Their recommendations emphasized the development of **benchmark datasets**, integration of **multimodal sentiment analysis** (text, audio, video), and improved **explainability of models** for practical adoption in education.

6. Comparative Insights Across Studies

From this body of work, several trends emerge:

1. **Shift in Technology**:
    - Early works (2017–2019) relied on **Naïve Bayes, SVM, and lexicon-based methods**.
    - Later works (2020 onwards) increasingly adopted **deep learning (LSTM, CNNs)** and **transformers (BERT, Indo-BERT)**.
2. **Accuracy Improvements**:
    - Traditional ML models achieved **70–85% accuracy**.
    - Deep learning approaches pushed accuracy to **87–89%**.
    - Transformer-based models (BERT) reached **91–96%**, representing state-of-the-art performance.
3. **Scope of Analysis**:
    - Early studies classified overall sentiment as **positive/negative/neutral**.
    - Recent works moved towards **Aspect-Based Sentiment Analysis (ABSA)**, capturing student views on specific dimensions (placements, faculty, infrastructure, etc.).
4. **Limitations Across Studies**:
    - Dependence on **large labeled datasets**.
    - Difficulty in handling **sarcasm, slang, and cultural variations**.
    - High **computational cost** of transformer models.
    - Limited generalizability beyond the dataset's language and region.

7. Conclusion

The evolution of sentiment analysis in the education domain reflects a clear transition from simple **lexicon and ML classifiers** to **sophisticated transformer-based ABSA models**. While traditional models offered accessibility and interpretability, their limited contextual understanding constrained accuracy. Transformer models like **BERT and Indo-BERT** deliver state-of-the-art results, offering nuanced insights into **aspect-level sentiments**, thereby empowering educational institutions to make informed, data-driven improvements.

However, challenges remain—particularly the need for **standardized multilingual datasets**, **low-resource model adaptations**, and **explainable AI systems** for educators. Future research should focus on integrating multimodal inputs, improving cultural adaptability, and balancing accuracy with computational efficiency.

RESEARCH OBJECTIVE

1. To investigate the impact of online reviews on institutional reputation

- Study how negative feedback influences prospective students' admission decisions and stakeholders' trust.
- Highlight the growing importance of reputation management for colleges in the digital era.

2. To collect, preprocess, and organize review datasets

- Gather reviews from various platforms such as Google Reviews, college portals, and social media.
- Apply preprocessing techniques such as tokenization, stop-word removal, stemming/lemmatization, and text normalization to prepare clean datasets suitable for analysis.

3. To implement sentiment analysis models for review classification

- Use supervised and unsupervised learning techniques to categorize reviews into positive, neutral, and negative.
- Compare traditional machine learning methods (Naïve Bayes, SVM, Logistic Regression) with deep learning models (RNN, LSTM, Transformers).

4. To perform Aspect-Based Sentiment Analysis (ABSA)

- Identify the specific aspects mentioned in negative reviews, such as faculty quality, infrastructure, placements, administration, or student facilities.
- Detect the polarity (positive/negative) associated with each aspect to better understand the root cause of dissatisfaction.

5. To design an automated response generation framework

- Develop a Natural Language Processing (NLP)-based system capable of producing empathetic, context-aware, and professional responses.
- Explore different approaches such as:
    - **Template-based methods** (predefined structured responses).
    - **Rule-based methods** (if-else logic with sentiment cues).
    - **Machine learning & transformer-based text generation models** (e.g., GPT, BERT variants).

6. To ensure empathetic and professional tone in responses

- Incorporate linguistic techniques that soften responses and maintain a constructive, student-friendly communication style.

- Prevent robotic or repetitive replies by ensuring diversity in generated responses.

7. To build a semi-automated approval mechanism

- Allow college administrators to review, edit, or approve auto-generated responses before posting them.
- Enable continuous improvement by training the system on corrected responses.

8. To evaluate system performance using multiple metrics

- Classification accuracy for sentiment detection.
- Precision, recall, and F1-score for aspect detection.
- BLEU/ROUGE scores, grammatical correctness, and semantic relevance for response generation.
- Human evaluation for empathy, professionalism, and usefulness of responses.

9. To measure the practical benefits of the system

- Reduction in response time compared to manual handling.
- Improved consistency and quality of communication with stakeholders.
- Contribution to reputation management and student engagement.

10. To propose a scalable and domain-independent framework

- Ensure the system can be generalized to other industries (healthcare, hospitality, e-commerce) where review management is critical.
- Provide adaptability for multilingual support and integration with real-time review monitoring platforms.

HARDWARE AND SOFTWARE REQUIREMENTS

1. Hardware Requirements

To ensure smooth development and execution of the project, the following minimum hardware specifications are recommended:

- **Processor (CPU):** Intel i5 / AMD Ryzen 5 or higher (for efficient model training and execution)
- **Memory (RAM):** 8 GB minimum (16 GB recommended for handling NLP models and large datasets)
- **Storage:** 256 GB SSD or higher (for dataset storage, logs, and model checkpoints)
- **Graphics Card (GPU):** NVIDIA GPU with CUDA support (optional but recommended for faster training of deep learning models)
- **Monitor & Peripherals:** Standard display, keyboard, and mouse
- **Internet Connectivity:** Required for dataset collection, dependency installation, and testing with online APIs

2. Software Requirements

Operating System

- Windows 10/11, Linux (Ubuntu 20.04+), or macOS

Backend & Development Frameworks

- **Python 3.8+** (primary programming language)
- **Django/Flask** (if web-based deployment is planned)

NLP & Machine Learning Libraries

- **NLTK** (Natural Language Toolkit – preprocessing, tokenization, stopword removal)
- **spaCy** (for advanced NLP tasks like dependency parsing, named entity recognition)
- **Scikit-learn** (for sentiment classification models)
- **TensorFlow / PyTorch** (for deep learning-based text generation models)
- **Transformers (Hugging Face)** (for pre-trained models like BERT, GPT, etc.)

Database

- **MySQL / PostgreSQL** (for storing reviews, responses, and user/admin data)

Other Tools & Utilities

- **Jupyter Notebook / Google Colab** (for experimentation and model training)

- **Git** (for version control)
- **VS Code / PyCharm** (for coding and debugging)
- **Docker (Optional)** (for containerization and deployment)
- **Postman (Optional)** (for API testing if deploying as a service)

PROJECT FLOW

The project follows a systematic flow that begins with collecting reviews and ends with generating automated responses for negative feedback. The key stages are:

1. **Data Collection**
    - Reviews are gathered from multiple sources such as college websites, review portals, and social media platforms.
    - Both positive and negative reviews are stored in the database for analysis.
2. **Data Preprocessing**
    - Raw reviews are cleaned and normalized.
    - Steps include tokenization, stop-word removal, stemming/lemmatization, and removal of irrelevant symbols/characters.
    - Preprocessed text is prepared for sentiment analysis and aspect detection.
3. **Sentiment Analysis**
    - Each review is classified into **positive, negative, or neutral** using machine learning or deep learning models.
    - Only **negative reviews** are passed to the next stage for response generation.
4. **Aspect-Based Sentiment Analysis (ABSA)**
    - The system identifies the specific aspect being criticized in the negative review (e.g., faculty, infrastructure, placements, administration, hostel facilities).
    - Helps generate a context-aware response instead of a generic reply.
5. **Automated Response Generation**
    - An NLP-based model (template-based + ML/Transformer-based) generates a draft response.
    - Responses are designed to be empathetic, professional, and relevant to the issue raised.
6. **Admin Review & Feedback (Optional)**
    - The draft response can be reviewed and edited by administrators before final posting.
    - The system continuously learns and improves by retraining on corrected responses.
7. **Response Delivery**
    - The approved response is published back on the platform (review portal, college website, or social media).

    - Students see their concerns addressed quickly, improving trust and satisfaction.

8. **Performance Evaluation & Insights**
    - System performance is evaluated using accuracy, precision, recall, and F1-score (for classification).
    - Generated responses are evaluated for grammar, relevance, and empathy (using BLEU/ROUGE scores and human evaluation).
    - Insights are provided to administrators on the most common issues raised by students, helping improve institutional services.

RESEARCH OUTCOME

The expected outcomes of this research project are:

1. **Automated Detection of Negative Reviews**
   - A working system capable of identifying and classifying negative reviews from large volumes of student feedback with high accuracy.
2. **Aspect-Based Insights**
   - Ability to pinpoint the exact issues raised (e.g., faculty, infrastructure, placements, hostel facilities, administration) rather than treating reviews as generic complaints.
3. **Automated Response Generation System**
   - A functional prototype that generates **context-aware, empathetic, and professional replies** to negative reviews, ensuring timely communication with stakeholders.
4. **Reduced Administrative Workload**
   - Significant reduction in manual effort required by placement cells or administrative staff to monitor and respond to reviews.
5. **Improved Communication Consistency**
   - Responses that maintain a professional and uniform tone, avoiding inconsistencies in style or quality across different reviewers.
6. **Enhanced Student Engagement and Trust**
   - Faster acknowledgment of concerns improves transparency, student satisfaction, and trust in the institution.
7. **Reputation Management Support**
   - Helps colleges maintain a positive digital presence by addressing grievances promptly and effectively.
8. **Actionable Data Insights**
   - Reports highlighting recurring problem areas, enabling institutions to take corrective measures and improve services.
9. **Evaluation Metrics and Benchmarks**
   - A set of quantitative (accuracy, precision, recall, BLEU/ROUGE scores) and qualitative (human evaluation of empathy and professionalism) metrics to assess the system’s effectiveness.

10. **Scalable Framework for Other Domains**

- A generalizable model that can be extended to other industries (e-commerce, healthcare, hospitality) where managing online reviews is equally important.

PROPOSED TIME DURATION

PHASE	TIME DURATION
Requirement Analysis & Literature Review	(Weeks 1–2)
Data Collection & Preprocessing	(Weeks 3–5)
Sentiment Analysis & Aspect Extraction	(Weeks 6–9)
Response Generation Model Development	(Weeks 10–13)
System Integration & Admin Module	(Weeks 14–15)
Testing & Evaluation	(Weeks 15–16)
Documentation & Report Writing	(Weeks 17–18)

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