



## Title

Student Grievance Categorization using Small Language Models

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# Motivation

Handling student grievances in universities is a complex and time-consuming process when done manually, often resulting in delays, dissatisfaction, and lack of transparency. Automating the categorization of grievances using a small language model can significantly speed up the resolution process, ensure accurate routing to the appropriate departments, and minimize human errors. This not only reduces the workload of administrative staff but also improves trust, accountability, and overall satisfaction among students by providing timely updates, fair handling, and a robust feedback mechanism.

# SCOPE of the Project

This project involves the development of an automated Student Grievance Categorization System using a small language model with the following key functionalities:

- A user-friendly interface allowing students to submit grievances.
- Automated classification of grievances into categories such as academic, hostel, and finance using a fine-tuned small language model.
- Routing grievances to the appropriate department or administrator based on classification.
- Provision of grievance status tracking for both students and administrative staff.
- Delivery of automated notifications to keep students informed of their grievance progress.
- Secure storage and management of grievance records ensuring confidentiality.
- Implementation of a feedback mechanism following grievance resolution.
- Utilization of annotated sample data for model development and evaluation.

The system is designed to streamline grievance handling processes, improve efficiency, and enhance transparency in student support services.

# Objectives

- ❑ To develop an automated system that efficiently categorizes student grievances into predefined categories such as academic, hostel, and finance.
- ❑ To provide students with a simple and accessible interface to submit grievances confidentially.
- ❑ To enable timely routing of grievances to the appropriate departments for faster resolution.
- ❑ To facilitate real-time tracking of grievance status by both students and administrators.
- ❑ To improve transparency and communication through automated notifications and updates.
- ❑ To securely store and manage grievance data while maintaining privacy and confidentiality.
- ❑ To incorporate a feedback mechanism to continually enhance the grievance handling process.
- ❑ To utilize data insights from grievances to help the institution identify recurring issues and improve policies.

# Literature Review: Critical Analysis

## 1.) Rachana Shekar Rao et al. (International Journal for Research in Applied Science & Engineering Technology – IJRASET, 2023):

- ❑ **Methodology:** Developed a speech-to-text pipeline using Natural Language Processing techniques. Preprocessing included stemming, tokenization, and stop-word removal. The main focus was converting grievances spoken in English into text for further analysis.
- ❑ **Findings:** Demonstrated that speech-based grievance entry can enhance accessibility for individuals who may not be comfortable with manual typing. The study successfully showed that automated transcription reduces manual effort.
- ❑ **Limitations:** The system lacked deeper layers such as classification, prioritization, and sentiment analysis. It also struggled with noisy inputs, diverse accents, and real-world speech irregularities. The work was essentially a proof-of-concept rather than a deployable grievance redressal system.
- ❑ **Critical Analysis:** While valuable for accessibility, the study is too narrow to address end-to-end grievance handling. It serves as a starting point but fails to close the loop on categorization and resolution.

## 2.) Er Binaya Subedi et al. (2024) – *Helijon (Elsevier)*:

- ❑ **Methodology:** Analyzed grievances from the Nepal government's "Hello Sarkar" portal using supervised machine learning algorithms like Naïve Bayes and SVM on ~3,000 multilingual grievances.
- ❑ **Findings:** Showed that multilingual public grievances can be classified effectively with supervised models.
- ❑ **Limitations:** Focused on public/government grievances, not student-specific issues; domain applicability to academic grievance systems is limited.
- ❑ **Critical Analysis:** Strong real-world application, but lacks adaptability to student domains. Offers insight into multilingual processing but needs domain customization.

### 3.) Onan, Atik and Yalçın (2021) – *Expert Systems with Applications* (Elsevier):

- ❑ **Methodology:** Used TF-IDF for text representation and applied classifiers like Naïve Bayes, k-NN, decision tree, SVM, and random forest on 17,831 university service requests.
- ❑ **Findings:** SVM achieved 92.26% accuracy, showing the potential of machine learning for automating request routing.
- ❑ **Limitations:** Focused on general university service requests rather than grievance redressal. Emotional and contextual aspects of complaints were not considered.
- ❑ **Critical Analysis:** Strong methodology with a large dataset, but misses the human and emotional side of grievances, which is crucial in student complaint systems.

### 4.) Taruc and De La Cruz (2024) – *International Journal of Advanced Computer Science and Applications (IJACSA)*:

- ❑ **Methodology:** Used pre-trained BERT model (“pysentimiento”) to analyze sentiment in student feedback regarding academic activities.
- ❑ **Findings:** Showed that transfer learning with BERT can provide meaningful insights even when trained on non-educational data.
- ❑ **Limitations:** Focused only on sentiment, not grievance classification. Computationally heavy and not easily scalable.
- ❑ **Critical Analysis:** Advanced and accurate, but too resource-intensive for direct use in simple grievance systems. Needs simplification for wider adoption.

##### 5.) Kondhare et al. (2021) – International Research Journal of Engineering and Technology (IRJET):

- ❑ **Methodology:** Developed a portal using deep neural networks for grievance classification, sentiment analysis, anonymity, and tracking.
  - ❑ **Findings:** Neural networks effectively categorized grievances and analyzed emotional tone while preserving anonymity.
  - ❑ **Limitations:** High computational cost makes it unsuitable for lightweight university portals; real-world deployment challenges were not addressed.
  - ❑ **Critical Analysis:** Technically strong and innovative, but not practical for smaller institutions with limited resources. It sacrifices accessibility for sophistication.
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Current research demonstrates that NLP and ML techniques are effective in digitizing and analyzing grievances. However, each approach has clear shortcomings.

Rule-based systems are too rigid and fail to handle unstructured student complaints. Government-oriented datasets, though useful, do not reflect the unique nature of academic grievances.

On the other hand, deep learning and transformer-based models like BERT provide high accuracy but require heavy computational resources, making them unsuitable for lightweight institutional setups. Therefore, there is a gap for a balanced system that blends accuracy with sentiment analysis while remaining scalable and efficient for academic environments.

# Gap identified

Current research demonstrates that NLP and ML techniques are effective in digitizing and analyzing grievances. However, each approach has clear shortcomings:

## **Limitations in Existing Systems:**

- ❑ Rule-based systems are too rigid and fail to handle unstructured student complaints with varied language patterns and informal expressions
- ❑ Government-oriented datasets, though useful, do not reflect the unique nature of academic grievances and student-specific terminology
- ❑ Deep learning and transformer-based models like BERT provide high accuracy but require heavy computational resources, making them unsuitable for lightweight institutional setups
- ❑ Lack of domain-specific solutions for academic environments that understand student language, university terminology, and academic context

# Gap identified

## **Key Research Gaps:**

- Most existing systems focus on general complaint handling rather than student-specific grievances
- Limited work on lightweight models suitable for university infrastructure constraints
- Insufficient attention to real-time processing needs in academic settings
- Missing integration of sentiment analysis with practical grievance routing

**Therefore, there is a clear gap for a balanced system that:**

- Blends accuracy with sentiment analysis while remaining scalable and efficient for academic environments
- Understands student language patterns and university-specific terminology
- Provides real-time classification suitable for institutional deployment
- Balances computational efficiency with classification accuracy

# Proposed Methodology

## Phase 1: Data Collection & Preprocessing

- ❑ Dataset Creation: Collect 500-1000 student grievance samples across three main categories:
  - Academic (exam issues, course problems, faculty concerns)
  - Hostel (accommodation, mess, facilities)
  - Finance (fee payments, scholarships, refunds)
- ❑ Data Preprocessing:
  - Text cleaning (remove special characters, normalize case)
  - Tokenization and stop-word removal
  - Handle student slang and informal language patterns

## Phase 2: Model Development

- ❑ Feature Extraction:
  - TF-IDF vectorization for capturing important terms
  - N-gram analysis (unigrams + bigrams) for context understanding
- ❑ Model Selection:
  - Start with Multinomial Naive Bayes (lightweight, interpretable)
  - Compare with Support Vector Machine (SVM) for better accuracy
  - Fine-tune hyperparameters using cross-validation

# Proposed Methodology

## Phase 3: Enhancement & Integration

- ❑ Sentiment Analysis: Integrate basic sentiment scoring to identify urgent/emotional grievances
- ❑ Confidence Scoring: Implement uncertainty detection for edge cases requiring human review
- ❑ API Development: Create REST API for integration with university systems

## Phase 4: Deployment & Evaluation

- ❑ Web Interface: Develop user-friendly submission portal using Streamlit/Flask
- ❑ Performance Metrics: Accuracy, Precision, Recall, F1-score across all categories
- ❑ Real-world Testing: Deploy pilot version with feedback collection mechanism

# Skills Required [What skills are known and what you planned to acquire]

## Known Skills (Current Team Capabilities):

- Programming: Python fundamentals, basic scripting, and data structures
- Machine Learning: Understanding of classification algorithms, train-test splits, and evaluation metrics
- Data Handling: Experience with pandas and numpy for data manipulation and analysis
- Text Processing: Basic text cleaning, tokenization, and preprocessing techniques
- Web Development: HTML/CSS basics and simple Flask applications

## Skills to Acquire During Project:

### **Advanced NLP Techniques:**

- TF-IDF vectorization and feature engineering for text representation
- Domain-specific text preprocessing for handling student language and slang
- N-gram analysis and feature selection for improved classification performance

# Skills Required [What skills are known and what you planned to acquire]

## **Model Development & Optimization:**

- Hyperparameter tuning using GridSearchCV and cross-validation
- Model evaluation techniques: confusion matrices, precision-recall analysis
- Handling imbalanced datasets and model interpretability methods

## **System Integration & Deployment:**

- REST API development using FastAPI or Flask for model serving
- Model serialization and loading techniques (pickle/joblib)
- Database integration for storing grievances and user data
- Basic web interface development for grievance submission portal

## **Project Management:**

- Git version control for collaborative development and code management
- Technical documentation writing and user manual creation
- Testing methodologies for ML models and web applications

# Preliminary Results

## Dataset Plan:

- Around 500-1000 initial grievance samples will be collected for each category.
- Data will include common complaints like “Exam timetable clashing”, “Mess food is bad”, “Fee payment delayed”.

## Planned Model:

- Text → Bag-of-Words using CountVectorizer.
- Multinomial Naive Bayes for text classification (lightweight & effective).
- 80–20 train-test split.
- Expected Initial Accuracy: ~80–85%

## Evaluation Metrics:

- Accuracy, Precision, Recall, F1-score.
- Confusion matrix to analyze misclassifications.

# Expected Outcome

Trained grievance classifier achieving  $\geq 90\%$  accuracy on expanded dataset (500–1000 samples).

Fast real-time classification: input grievance  $\rightarrow$  instant category (Academic, Hostel, Finance).

## Impact:

- Reduces manual sorting time by 60–70%.
- Enables automated routing to relevant departments.

## Deployment Plan:

- Simple web app (Streamlit/Flask) or command-line tool for demo.