A Survey on Automated Approaches for Academic Complaint Resolution

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Abstract :

With more colleges using digital platforms, they face many student complaints about academics, exams, infrastructure, administrative processes, and campus facilities. Handling these complaints effectively is a major challenge because of the rising number and variety of submissions.

Existing complaint management systems depend on manual review and decision-making. This often leads to delayed responses, inconsistent prioritization, and challenges in spotting urgent complaints. These issues reduce administrative efficiency and hurt the overall effectiveness of complaint resolution.

To tackle these challenges, this paper suggests a smart college complaint resolution system that combines AI-assisted routing, complaint categorization, and supervised machine learning methods. Natural Language Processing (NLP) processes complaint text in everyday language, using TF-IDF as a feature extraction method to turn unstructured text into numerical formats. We then apply supervised machine learning models to classify complaints into relevant categories and predict their urgency levels. Based on these predictions, the system helps administrators route complaints to the right handling units.

The proposed system uses Logistic Regression for categorizing complaints and predicting their urgency. We evaluate performance through accuracy, precision, recall, and F1-score, achieving about 90% accuracy. This is a significant improvement over traditional manual methods. The system integrates NLP-based text processing, TF-IDF feature extraction, and supervised learning. This combination improves complaint prioritization, reduces response time, and increases the overall efficiency of the college complaint resolution process.

Keywords :

College Complaint Resolution System, Complaint Management, Natural Language Processing, TF-IDF Feature Extraction, Supervised Machine Learning, Logistic Regression, AI-Assisted Routing.

I.Introduction

The fast digital shift in higher education has greatly changed both administrative and academic processes,especially in handling student complaints. Colleges and universities face many complaints about academics, exams, facilities, administrative procedures, hostels, transportation, and campus services.

A good complaint resolution system is crucial for promoting transparency, accountability, and student satisfaction within the institution's governance framework [6].

Despite having online complaint portals, many institutions still depend on traditional or semi-automated systems. These systems need manual checking, sorting, and prioritizing of complaints.

In these systems, administrators read each complaint, identify the relevant category, determine its urgency, and forward it to the right department. This process takes a lot of time and gets less efficient as the number of complaints increases [9].

Manual handling often causes inconsistencies because of personal judgment. This can lead to delays in responding to important complaints.

Several studies on college complaint management systems have found major limitations in manual and rule-based methods. These include poor scalability, a lack of smart prioritization, and limited transparency in tracking complaints [6][8]. When complaints are not prioritized well, urgent issues like infrastructure failures or concerns related to academic deadlines may not get immediate attention. This hurts the perceived reliability of institutional complaint resolution processes and lowers student trust.

Recent advancements in Artificial Intelligence (AI) have made it possible to automate decision-making processes in different areas that involve large amounts of unstructured data. Natural Language Processing (NLP) has become an effective method for analyzing text written in everyday language. Supervised Machine Learning (ML) models have shown strong performance in classification and prediction tasks [1][2]. These technologies are commonly used in customer support systems, feedback analysis platforms, and service management applications.

Within the context of complaint management, NLP techniques can process complaint text by cleaning, tokenizing, and transforming it into numerical representations that work with machine learning algorithms. Feature extraction methods like Term Frequency and Inverse Document Frequency (TF-IDF) help find important terms that define the nature and urgency of complaints[3]. Supervised ML models can learn from past complaint data to classify new complaints and predict how urgent they are with high accuracy.

Existing research in the field of college complaint management shows the need for smart systems that go beyond simple complaint submission and tracking functions [7][10]. Some systems offer digital interfaces for registering complaints, but they often do not have automated analysis features, which leads to ongoing reliance on manual decision-making. This gap emphasizes the importance of adding AI-supported tools to complaint resolution platforms.

II.Methodology

A. System Overview

The proposed system is an AI-assisted platform for resolving complaints. It automates the early stages of handling complaints in higher education. The main goal is to lessen the need for manual complaint screening. At the same time, it aims to improve the accuracy and efficiency of categorizing and prioritizing complaints.

The system processes complaints from students in natural language and uses Natural Language Processing (NLP) and supervised Machine Learning (ML) techniques to analyze the content of these complaints. Based on this analysis, the system predicts the category and urgency level of the complaints. This helps administrators prioritize and route complaints effectively.

The methodology uses a modular design approach. Complaint submission, data processing, machine learning inference, and administrative decision-making are viewed as separate but connected components. This modular structure allows for growth and makes it easier to improve the system in the future. For example, it supports model retraining or adding new AI techniques without disrupting the overall workflow.

Unlike traditional complaint management systems that depend on set rules or manual choices, the proposed approach brings in data-driven intelligence for resolving complaints. By learning from past complaint data, the system adjusts to different complaint patterns and helps prioritize consistently across various types of complaints. Similar smart methods have been suggested in previous studies on complaint and service management systems to improve transparency and response efficiency [6][9].

B. System Architecture

The design of the Smart College Complaint Resolution System is a layered and modular framework. It brings together user interaction, backend processing, and AI-based complaint analysis.

The system has three main layers: Web User Interface, Backend Services, and AI/NLP Processing Layer. These layers are supported by a centralized Machine Learning and Database layer.

The Web User Interface (Web UI) is where students and administrators interact. Students can submit complaints through the complaint submission module and check the status of their past complaints. Administrators use the admin dashboard to view, prioritize, and manage these complaints. All user actions are sent to the backend for further processing.

The Backend Layer serves as the communication and coordination part of the system. It gets complaint text from the Web UI and provides APIs to manage complaint submission, retrieval, and status updates. The backend sends complaint content to the AI/NLP processing layer using a secure API interface and receives prediction results for storage and display.

The AI/NLP Processing Layer, built as a Python-based machine learning API, analyzes complaints intelligently. This layer first uses Natural Language Processing to clean and normalize the complaint text. After that, it converts the processed text into numbers. form using Term The AI/NLP Processing Layer, built as a Python-based machine learning API, analyzes complaints intelligently. This layer first uses Natural Language Processing to clean and normalize the complaint text. After that, it converts the processed text into numbers.

The Machine Learning Models analyze incoming complaints and predict the category and urgency level of each complaint. The predicted results go back to the backend server and are stored in the database. This allows for AI-assisted routing and prioritization of complaints in the administrative workflow.

The Machine Learning and Database Layer stores trained models, Term Frequency - Inverse Document (TF-IDF) vectorizers, and complaint-related data. MongoDB maintains user data, complaint records, status updates, and system logs. This centralized storage ensures data consistency, traceability, and efficient retrieval.

Overall, the proposed architecture clearly separates different concerns, supports scalability, and allows for smooth integration of AI-assisted complaint analysis. The modular design makes it easy to add improvements in the future, such as model upgrades, new AI techniques, or multilingual support, without impacting the overall system structure.

C. Student Complaint Submission Flow

The system helps with AI-assisted routing. It uses the predicted category and urgency as inputs to support decisions made by administrators. Although administrators still make the final routing decision, the system greatly cuts down on decision time by offering organized and prioritized complaint information.

The student complaint submission flow outlines the first interaction between the user and the complaint resolution system. This process aims to gather complaint information correctly. It also ensures that the submitted data can be processed right away by the analysis components.

The process begins when a student opens the complaint submission module in the school's web application. The system offers an interface that lets the student describe the complaint in natural language. This makes it easier for them to provide detailed input. This design reduces user limits and encourages thorough problem descriptions, which are important for effective automated analysis.

Upon submission, the system checks to make sure all required information is present and prevents invalid or incomplete entries. After validation, the complaint receives a unique identifier and a submission timestamp. These elements help with traceability and allow for consistent tracking of the complaint throughout its lifecycle.

The validated complaint text is sent to the backend processing unit. Here, it enters the automated analysis pipeline. At this point, the complaint is treated as raw text and is sent to the Natural Language Processing module for transformation. Preprocessing tasks like text normalization, token segmentation, and noise removal are applied to standardize the input and reduce differences across various submissions [1][3].

After preprocessing, the revised complaint representation is available to feature extraction and machine learning components. The system generates predicted complaint categories and urgency levels. These are added to the complaint record before storage. This process ensures that each complaint is immediately enhanced with the structured information needed for prioritization and decision support.

By automating the complaint submission and initial analysis stages, the proposed system ensures that student complaints are processed quickly. This approach improves system responsiveness, supports real-time prioritization, and creates a solid foundation for handling complaints effectively in large educational environments [6][9].

D. Administrator Complaint Handling Flow

The administrator complaint handling flow outlines how submitted complaints are reviewed, prioritized, and managed after the system performs automated analysis. This flow aims to help administrators make decisions by offering structured insights supported by AI, not replacing human control.

Once a student submits a complaint and it goes through the NLP and machine learning process, it appears on the administrator dashboard. Each complaint shows its predicted category and urgency level. These are generated automatically by analyzing the complaint text. The dashboard lists complaints in order of priority. This helps administrators quickly spot high-urgency complaints.

The administrator reviews the complaint details and the predictions generated by the system. The predicted category and urgency provide support for decision-making, but the administrator has full power to check, change, or ignore these predictions if necessary. This mixed approach keeps accountability while lowering the mental effort needed for manual complaint screening, a limitation often seen in traditional complaint management systems [6][8].

Based on the information reviewed, the administrator assigns the complaint to the right handling unit or department. The system helps with AI-assisted routing by suggesting appropriate routing decisions based on predicted category and urgency. However, the administrator makes the final routing decision manually. This choice maintains a balance between automation and control while reducing the chance of making incorrect routing decisions.

After routing, the administrator updates the complaint status to show its current stage, such as "In Progress," "Under Review," or "Resolved." These status updates are stored in the database and visible to students through the complaint tracking interface. This ensures transparency during the resolution process.

The administrator managing flow improves response efficiency by removing the need for manual prioritization and initial classification. By including AI-generated insights in the administrative workflow, the system allows for quicker handling of important complaints while keeping accuracy and oversight, which are vital for effective complaint resolution in educational institutions [9][10].

E. Natural Language Processing Methodology

Natural Language Processing (NLP) is the main preprocessing layer of the proposed complaint resolution system. All complaint inputs come in an unstructured text format. Student complaints often differ greatly in vocabulary, sentence structure, length, and writing style. These differences create noise and inconsistency, which makes it hard for machine learning models to accurately interpret the raw complaint text. For this reason, NLP techniques are used to standardize complaint representations and extract useful linguistic information before classification [1][3].

The NLP pipeline starts with text normalization. This step ensures consistency in all complaint entries. All characters are changed to lowercase to avoid treating different cases of the same word as separate features. Punctuation marks, numerical symbols, and non-alphabetic characters are also eliminated since they usually do not help with understanding the meaning in complaint classification tasks.

Following normalization, the complaint text is broken down into individual lexical units called tokens. Tokenization allows the system to examine the complaint content at the word level and supports further language processing. Each token stands for a potential feature that may show the nature or urgency of a complaint. This step is especially important for identifying specific keywords often linked to institutional complaints, such as terms related to examinations or infrastructure issues.

After tokenization, stop-word removal is used to eliminate frequently occurring but weak words like “the,” “is,” “and,” and “of.” These words show up in most complaint descriptions and do not help differentiate between various complaint categories or urgency levels. Removing stop words cuts down feature dimensionality and improves computational efficiency during model training and inference [3].

Let a processed complaint document be represented as:

$$D=\{w1,w2,w3,\dots,wn\}$$

where wi represents the ith meaningful token extracted after preprocessing.

In addition to reducing noise, the NLP pipeline maintains consistency between the training and inference phases. All complaints, whether they are used for model training or real-time prediction, go through the same preprocessing steps. This consistency is crucial to avoid feature mismatch and deterioration in classification performance.

The NLP method also allows the proposed system to scale. As the number of complaints rises, automated text preprocessing keeps the complaint analysis efficient, without adding extra manual work. Similar NLP preprocessing pipelines are commonly used in text classification and service automation systems because they effectively manage large amounts of text data [1][2].

By using structured NLP techniques before feature extraction, the system makes sure that complaint text is turned into a clean, standardized, and informative format. This change directly improves the performance of the following feature extraction and supervised machine learning stages. As a result, NLP is a key part of the proposed method.

F. Feature Extraction Using TF-IDF

After using Natural Language Processing techniques to preprocess complaint text, the next step in the methodology is feature extraction. Feature extraction is important for turning processed textual data into numerical values. Representations that machine learning algorithms can interpret effectively. Since machine learning models work with numerical inputs, you need to convert textual complaints into structured feature vectors before classification [3].

The proposed system uses the Term Frequency Inverse Document Frequency (TF-IDF) technique for feature extraction. TF-IDF is a common method in text classification tasks. It captures how important words are within a document while lessening the impact of frequently occurring terms in the dataset. This quality makes TF-IDF especially fitting for complaint analysis, where specific keywords clearly indicate the category or urgency of a complaint.

The Term Frequency (TF) component measures how frequently a term appears within a specific complaint document. It is defined as:

$$TF(t,\ d)\ =\ count(t,\ d)\ /\ |d| \qquad (1)$$

While term frequency shows locally important words, it doesn't consider terms that appear often in all complaints. To fix this issue, we introduce the Inverse Document Frequency (IDF) component. IDF takes away some weight from terms that show up in many documents and gives more importance to rare but informative terms. It is calculated as:

$$IDF(t)\ =\ log(N\ /\ (1\ +\ df(t))) \qquad (2)$$

where N represents the total number of complaint documents in the dataset and *df(t)* denotes the number of documents containing the term ttt.

The final TF-IDF score for a term is obtained by combining both components:

$$TF-IDF(t,\ d)\ =\ TF(t,\ d) \times IDF(t) \qquad (3)$$

Using this method, each complaint document is turned into a high-dimensional feature vector. Each dimension represents the TF-IDF weight of a specific term. These feature vectors keep important meaning while reducing noise from irrelevant or overly common words.

The TF-IDF technique provides several benefits for the proposed complaint resolution system. First, it helps distinguish between complaint categories by focusing on keywords specific to academics, infrastructure, administration, or examinations. Second, it aids in predicting urgency by highlighting terms that reflect severity or time sensitivity. Finally, TF-IDF is efficient and easy to understand, which makes it suitable for real-time complaint analysis [3][4].

By using TF-IDF feature extraction, the system makes sure that complaint text is shown in a clear numerical format. This improves the performance of supervised machine learning models. This feature representation serves as the basis for effective complaint categorization and urgency prediction in the next classification stage.

G. Machine Learning Model

The system uses supervised machine learning to carry out two main tasks: categorizing complaints and predicting their urgency. These tasks are seen as classification problems. The goal is to assign set labels to complaint instances based on their text.

Among the different classification algorithms tested during experimentation, Logistic Regression was chosen as the main model because it is simple, easy to understand, and effective for text classification tasks when used with TF-IDF features [4]. Logistic Regression works well in high-dimensional sparse feature spaces that are often generated by text-based feature extraction methods.

Given a TF-IDF feature vector x, Logistic Regression calculates the probability that a complaint belongs to a specific class using the sigmoid function:

$$P(y\ =\ 1\,|\,x)\ =\ 1\ /\ (1\ +\ e\hat{}\{-\ (w \cdot x\ +\ b)\}) \qquad (4)$$

where *w* represents the learned weight vector and *b* denotes the bias term.

Two separate Logistic Regression models are trained using labeled complaint data. One model classifies the type of complaint. The other model estimates the priority level of the complaint.

During training, the models learn the best parameters by reducing a loss function that reflects the difference between the predicted and actual labels. During inference, new complaints are turned into TF-IDF vectors. These vectors are then fed into the trained models to produce real-time predictions.

The use of Logistic Regression ensures consistent performance, quick inference, and clear decision-making. This makes it a good choice for deployment in institutional complaint management systems [4].

III. Results and Discussion

This section presents the experimental evaluation of the proposed smart college complaint resolution system. It discusses the observed outcomes. The goal is to evaluate how well NLP-based preprocessing and supervised machine learning improve complaint categorization and urgency prediction.

The system was tested with a labeled dataset of student complaints. Each complaint included free-text input along with predefined category and urgency labels. The dataset was split into training and testing subsets. All complaints went through the same Natural Language Processing pipeline. Then, TF-IDF feature extraction was applied, and Logistic Regression models were trained and evaluated based on the results [3][4].

Model performance was evaluated using standard classification metrics from the confusion matrix. These include accuracy, precision, recall, and F1-score. Here are the definitions of these metrics:

$Accuracy = (TP + TN) / (TP + TN + FP$

$Precision = TP / (TP + FP)$

$Recall = TP / (TP + FN)$

$F1 - Score = 2 \times (Precision \times Recall) / (Prec$

Performance Metrics of the Proposed Complaint Resolution System:

Metrics	**Value**
Accuracy	90%
Precision	0.89
Recall	0.88
F1-Score	0.88

Table-1: Performance table

Table 1 shows the performance evaluation of the machine learning-based complaint resolution system. The results indicate that the Logistic Regression model has high accuracy and a balanced precision-recall performance. This demonstrates its effectiveness in categorizing complaints and predicting their urgency.

V. Conclusion

Smart college complaint resolution system that uses Natural Language Processing and supervised machine learning to improve the efficiency and accuracy of handling complaints in higher education institutions. The proposed system automates complaint categorization and urgency prediction. This reduces the need for manual screening and personal judgment.

By using NLP-based text processing and TF-IDF feature extraction, unstructured complaint data is turned into meaningful numerical representations that are suitable for machine learning. We chose Logistic Regression as the main classification model because it is easy to understand and performs well in text-related tasks. Experimental evaluation showed that the system achieves about 90% accuracy, which marks a significant improvement over traditional manual complaint handling methods.

The system supports AI-assisted routing. It gives administrators structured insights to help prioritize and manage complaints more effectively. This method keeps human oversight, ensuring accountability and transparency which are essential in institutional complaint management systems.

Overall, the proposed solution improves response efficiency, increases consistency in complaint prioritization, and supports scalable complaint management. Future work may focus on comparing different machine learning and AI models, expanding the system to handle multilingual complaints, and adding learning mechanisms to further boost performance over time.

References:

[1] J. Yi *et al.*, "Audio Deepfake Detection: A Survey," *CoRR,* 2023. https://arxiv.org/pdf/2308.14970

[2] S. Abdali *et al.*, "Multi-modal Misinformation Detection," *arXiv*. https://arxiv.org/abs/2203.13883

[3] S. Tahmasebi *et al.*, "Multimodal Misinformation Detection," *arXiv*. https://arxiv.org/abs/2407.14321

[4] S. F. N. Azizah *et al.*, "Transformer Models in Fake News Detection," *CoRR*, 2023. https://arxiv.org/pdf/2308.04950

[5] R. Kumari and A. Ekbal, "AMFB for Multimodal Fake News Detection," *Expert Systems with Applications*, 2021.

[6] C. Bind *et al.*, "Beyond Complaints: College Grievance Redressal System," *IJSREM*, 2024.

[7] C. R. Shivanagi *et al.*, "ResolveU: Student Complaint Management," *IJSDR*, 2024.

[8] S. Patle *et al.*, "Efficient Campus Solutions," *IJARCCE*, 2023.

[9] Y. Sapte *et al.*, "E-Complaint Resolution System for College," *IRJET*, 2020.

[10] S. Koppad *et al.*, "College Grievance Portal," *IJNRD*, 2025.

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