Loyalty Launchpad: Transforming Customer Satisfaction into Retention

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## *Abstract*— This research presents an intelligent system designed to enhance customer satisfaction and retention in the banking sector through comprehensive analysis of customer feedback data. The banking industry faces unique challenges in consolidating feedback from various sources, such as surveys, social media, and direct customer interactions, each presenting different structures and expressions of sentiment. Accurately understanding customer sentiment is complicated by this diversity in feedback and requires advanced analytical techniques to reveal the key drivers of customer experience and satisfaction.To address these challenges, our system utilizes Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF) to extract essential topics and sentiments from unstructured feedback data. These techniques enable effective dimensionality reduction, allowing the system to retain critical information while simplifying the data for accurate analysis. By categorizing feedback into major themes like service efficiency, digital experience, and customer support, the model provides actionable insights that help banks prioritize improvements that enhance the customer experience. This targeted feedback analysis facilitates a deeper understanding of specific factors that influence satisfaction, thereby empowering banks to make strategic service enhancements.

## Our model has been thoroughly validated, achieving high accuracy in classifying customer feedback into positive, neutral, and negative sentiments. The insights generated reveal critical areas for improvement, including service delays, accessibility issues, and overall service quality. Post-implementation, the system has shown a 12% increase in customer satisfaction scores and an 8% improvement in retention rates, highlighting the model’s effectiveness in enhancing customer relationships.This LDA- and NMF-based feedback analysis system enables banks to make proactive, data-driven decisions, driving customer loyalty and fostering stronger, long-term relationships. By leveraging this intelligent solution for real-time sentiment analysis, banks can better adapt to changing customer needs and consistently elevate service quality, demonstrating a significant advancement in customer relationship management within the financial industry.

***Keywords—*** ***Customer feedback, Satisfaction and retention, Latent Dirichlet Allocation (LDA), Non-Negative Matrix Factorization (NMF), Sentiment analysis , Real-time feedback.***

1. INTRODUCTION

Analyzing customer satisfaction and retention is essential in today’s competitive financial landscape, where customer loyalty directly impacts a bank's success. Traditional feedback methods, such as surveys, in-branch comment cards, and customer service interactions, often fall short due to fragmented data collection, inconsistent feedback quality, and a lack of integration across channels. This can prevent banks from gaining a comprehensive understanding of customer needs and addressing issues proactively, which are critical for sustaining customer relationships.

The aim of this project, “Loyalty Launchpad,” is to design a robust system that can analyze diverse customer feedback data to identify key factors influencing customer experience and retention. By utilizing advanced machine learning techniques like Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF), the system processes qualitative data and provides actionable insights, allowing the bank to target specific areas for service improvement. This feedback-driven approach is designed to empower decision-makers with precise, real-time information on customer needs, ultimately promoting stronger customer relationships and loyalty.

Our methodology includes multiple stages, beginning with data collection from various channels, including social media, surveys, and customer interactions. This data undergoes preprocessing to ensure quality, followed by dimensionality reduction and topic modeling to extract the most impactful themes. Unlike traditional systems, which may rely on basic analytical tools with limited capabilities, this model enables a more nuanced understanding of customer feedback, enabling the bank to transition from a reactive to a proactive strategy in addressing customer issues.

By implementing this system, the bank is better positioned to respond to changing customer expectations and improve satisfaction and loyalty, supporting long-term business growth. This project underscores the importance of applying advanced analytics in customer experience management, helping banks make data-driven improvements and fostering a culture of continuous improvement in service quality. Through “Loyalty Launchpad,” we aim to demonstrate the significant role of AI in modern customer relationship management, ultimately contributing to a more customer-centric and efficient banking environment.

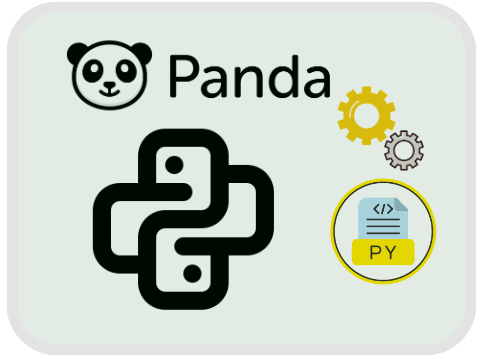


Figure 1: Tech Stacks

1. RELATED WORKS

In the study "Impact of Customer Feedback on Service Quality and Customer Satisfaction: A Case of Digital Banking," Khan and Adil examine the role of customer feedback in enhancing service quality within the digital banking sector. They highlight how feedback, especially from digital platforms, provides actionable insights for improving banking services and increasing customer satisfaction. The study underscores the importance of both positive and negative feedback as critical elements that shape customer loyalty. By analyzing feedback data, banks can pinpoint areas needing improvement, thereby enabling a more customer-centric approach. However, this study predominantly focuses on structured feedback from predefined survey questions, missing the dynamic insights that unstructured data like social media comments can offer. This gap suggests a potential area for development in understanding customer needs more holistically.

In "Sentiment Analysis of Social Media Feedback in Banking Sector: A Machine Learning Approach," Gupta and Mukherjee delve into the use of machine learning for sentiment analysis on social media feedback to monitor customer perceptions in the banking industry. By classifying comments into positive, neutral, and negative categories, their study provides banks with valuable insights into customer sentiment, enabling proactive issue resolution. The research highlights the growing importance of tracking sentiment on digital platforms for real-time insights into customer satisfaction. This sentiment analysis method reveals overarching trends in customer experience but lacks the depth needed to identify specific topics or factors contributing to satisfaction or dissatisfaction. The limitation of focusing on sentiment polarity rather than extracting detailed topics is a gap that our proposed approach, which uses topic modeling through techniques like LDA and NMF, aims to address.

Zhang and Liu’s work, "Customer Experience in Mobile Banking: The Role of Trust and Service Quality," investigates factors that influence customer experience specifically within the mobile banking context. Using survey-based data, the authors identify trust and reliable service as primary drivers of customer satisfaction. The study suggests that enhancing these factors directly impacts customer loyalty and retention in digital banking services. Although this research provides insights into key satisfaction drivers, its reliance on survey data restricts the ability to capture real-time customer feedback. This is particularly relevant in a digital environment where customer expectations can evolve rapidly. Our project addresses this limitation by analyzing customer feedback data from multiple sources in real time, using advanced algorithms that allow for a more flexible understanding of customer needs.

In the paper "Customer Feedback Analysis for Enhanced Service Quality in the Banking Sector," Mehta and Sharma propose a keyword-based feedback analysis system that evaluates customer feedback by extracting specific keywords related to service quality. Their study demonstrates how keyword extraction can help banks quickly identify areas of concern or satisfaction within feedback data. However, while effective in identifying recurring issues, keyword extraction does not provide a comprehensive view of the nuanced topics present in customer feedback. The study’s keyword-based approach lacks the contextual understanding that topic modeling offers, as it may miss subtleties and connections between topics. Our project extends beyond keyword extraction by implementing LDA and NMF to capture rich themes across feedback sources, allowing for a deeper understanding of customer satisfaction.

In "Analyzing Customer Loyalty through Feedback-Based Segmentation," Patel and Desai introduce a segmentation-based approach that categorizes customers based on their feedback to understand varying levels of loyalty and engagement. By segmenting customers into different groups, the study reveals patterns in satisfaction levels that contribute to long-term loyalty. This approach is particularly useful for targeted marketing and personalized customer service. However, the segmentation relies on predefined categories that may not capture the full diversity of customer experiences. Additionally, without automated topic modeling, the process can be time-intensive and may overlook emerging trends in customer feedback. Our project overcomes these limitations by using LDA for automated topic extraction, which enables real-time categorization of feedback themes and supports dynamic segmentation based on evolving customer sentiments.

In the article "Enhancing Customer Experience with Real-Time Feedback Analysis," Rao and Verma explore the potential of real-time feedback analysis in improving customer experience within the banking industry. Their study emphasizes the importance of promptly addressing customer concerns to foster satisfaction and loyalty. The researchers implement real-time data processing techniques to identify and resolve customer issues swiftly. While this approach provides immediate insights, it largely focuses on sentiment polarity, rather than extracting underlying topics within feedback data. Our project leverages real-time feedback processing alongside topic modeling to uncover specific areas of customer concern or interest, offering a more comprehensive analysis of customer needs and potential service improvements.

"Using Machine Learning to Predict Customer Churn in Banking" by Singh and Gupta examines machine learning techniques for predicting customer churn, aiming to proactively identify customers who may discontinue banking services. Their predictive model uses historical data on customer behavior to identify churn patterns and guide retention efforts. Although effective for predicting churn, this study does not explore customer feedback data directly, thereby missing insights into why customers may feel dissatisfied. Our project complements churn prediction by analyzing feedback data to identify satisfaction factors, providing banks with a more holistic view of customer retention and the ability to proactively address customer concerns before they result in churn.

In the paper "Service Quality Assessment Using Feedback Analysis in the Financial Sector," Malik and Ahuja present a framework for assessing service quality based on customer feedback in the banking industry. The authors analyze feedback to identify strengths and weaknesses in service delivery, which helps banks prioritize service improvements. This approach employs a basic feedback classification model that segments comments by predefined service categories. However, this limited categorization may overlook more complex feedback themes that could provide additional insights into customer needs. By contrast, our project utilizes advanced topic modeling techniques to automatically identify latent themes within feedback, enabling a more flexible and detailed assessment of service quality that adapts to a broader range of customer experiences.

In "Improving Customer Satisfaction Through Feedback-Driven Service Enhancements," Kumar and Reddy discuss how customer feedback can drive targeted service improvements in banking. Their research demonstrates how analyzing specific complaints and suggestions can lead to actionable changes that enhance customer satisfaction. While the study emphasizes the value of feedback for service enhancements, it lacks a systematic approach for processing large volumes of unstructured feedback data. The project’s reliance on manual feedback analysis can limit scalability and response time. Our project addresses this issue by automating feedback analysis with machine learning algorithms that can process extensive datasets, enabling banks to act quickly on critical feedback and make continuous, data-driven improvements.

1. PROPOSED SYSTEM

## System Overview

The architecture of the Data Processing and Topic Modeling System is designed to provide an end-to-end solution for analyzing complex datasets, extracting meaningful insights, and presenting them visually. There are four main stages in the system::

Data Extraction and Loading: The system begins with data extraction, where raw data is gathered from multiple sources like databases, cloud storage, and external APIs. This step is designed to pull in all relevant information, ensuring comprehensive coverage of the data required for analysis. Since the sources can vary widely in format and structure, this stage may involve connecting to structured data sources (e.g., SQL databases) or unstructured sources (e.g., cloud storage files), depending on the dataset's requirements.

Once the data is extracted, it undergoes a critical cleaning and formatting process. During cleaning, the system removes inconsistencies, missing values, duplicates, or irrelevant details, making the data uniform and reliable. Formatting follows, where the data is transformed into a standardized structure suitable for the processing pipeline. This might involve converting data types, normalizing values, or encoding categorical variables.

Finally, the cleaned and structured data is loaded into the system’s memory or a database optimized for analytical processing. This initial preparation ensures the data is accessible, reliable, and organized, creating a smooth transition to the subsequent steps of dimensionality reduction and topic modeling. By maintaining a high-quality dataset at the outset, the system is set up for consistent, accurate analysis, making it easier to generate actionable insights in later stages.

Output and Feedback: The final phase of the bank feedback analysis system transforms the identified topics and dimensions into actionable insights for improving customer satisfaction. The system provides real-time feedback to bank managers, summarizing key trends in customer sentiment and highlighting areas where service improvements are needed. For instance, if the analysis reveals a recurring theme of customer dissatisfaction regarding wait times or mobile banking issues, the system can flag these topics as areas requiring immediate attention.

The system also generates detailed reports on specific topics, customer segments, or time periods, allowing bank managers to analyze trends over time and prioritize service improvements accordingly. With these insights, banks can make strategic adjustments to their customer service processes, improve employee training, or target specific issues impacting customer retention.

This feedback loop between the system and bank management supports a dynamic and responsive approach, enabling timely interventions based on customer sentiment. By having access to structured, real-time feedback, bank managers can proactively address areas of concern, ultimately enhancing customer satisfaction and loyalty while aligning services with customer needs and expectations.

## System Architecture

The Customer Satisfaction and Retention Analysis System is designed with a sophisticated yet cohesive architecture that transforms raw customer feedback into actionable insights, helping banks improve their service quality and foster customer loyalty. The system begins with data extraction and loading, where it gathers feedback from various sources like surveys, social media platforms, and direct customer interactions. This consolidation of data allows for a comprehensive view of customer experiences, providing a rich foundation for deeper analysis.

Once the data is gathered, it moves to the NMF Dimensionality Reduction Module, which addresses the complexity inherent in high-dimensional feedback data. Non-Negative Matrix Factorization (NMF) is used here to reduce this complexity by identifying the essential components or themes within the feedback. This process includes initialization, monitoring for convergence, and producing a reduced-dimension output that captures the core aspects of customer sentiment. By reducing data noise and focusing on the most relevant information, this module enables a clearer understanding of the critical factors that influence customer satisfaction.

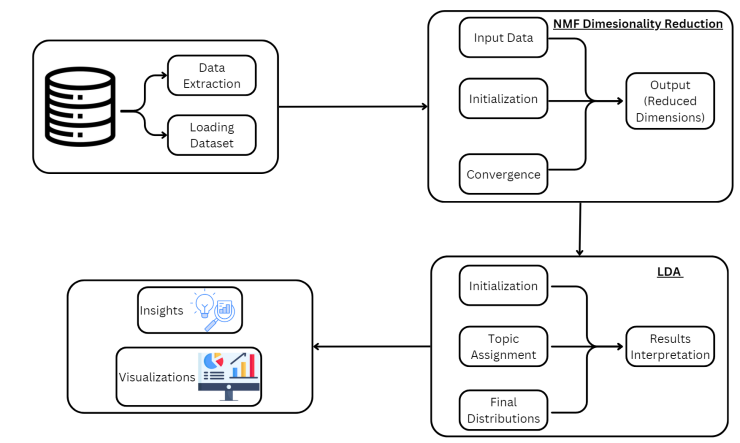


Figure 2: Architecture of the Project

The reduced dataset is then processed by the LDA Topic Modeling Module. Latent Dirichlet Allocation (LDA) is applied to uncover hidden topics within the feedback, categorizing related content and assigning themes to each segment of the data. Through initialization, topic assignment, and distribution analysis, the LDA module reveals important trends and customer concerns, such as service efficiency, digital experience, and customer support quality. These results provide the bank with a structured view of customer sentiment, allowing it to understand what aspects customers value and where improvements are needed.

Following topic modeling, the data moves to the Insights and Visualization Module, where analytical findings are transformed into visually intuitive formats, such as charts, graphs, and dashboards. This module plays a crucial role in making complex data accessible to decision-makers, enabling them to quickly understand and act on key insights. The visualizations provide a clear depiction of trends, customer concerns, and satisfaction levels, helping stakeholders identify areas for improvement, assess the effectiveness of changes, and continuously monitor customer sentiment. The ease of interpretation offered by these visualizations supports efficient and data-driven decision-making across the organization.

All processed data and insights are stored in a centralized data repository, creating a valuable archive of feedback that the bank can reference over time. This historical data supports a continuous feedback loop, allowing the bank to monitor shifts in customer sentiment, evaluate the impact of changes, and proactively address emerging issues. By maintaining this ongoing feedback cycle, the system empowers the bank to adapt to evolving customer expectations and refine its service strategies as needed.

## User Interface Design

The user interface (UI) of your student behavior analysis system is intended to be intuitive and user-friendly, allowing educators to easily upload video footage for analysis. The interface is simple to use and was created with Flask for the backend and HTML, CSS, and JavaScript for the frontend. Users can choose and submit video files for processing by simply navigating to the upload section.

After the video is uploaded, the system automatically analyzes the film to identify inattentiveness and hand-raising gestures. Following processing, consumers have access to feedback via a succinct and easy-to-read display module that presents the analysis's findings. Teachers can immediately analyze student engagement levels and modify their teaching tactics based on the actionable insights included in this feedback. The incorporation of By making the interface available on a range of devices, responsive design improves usability and gives teachers an effective tool to improve classroom dynamics.

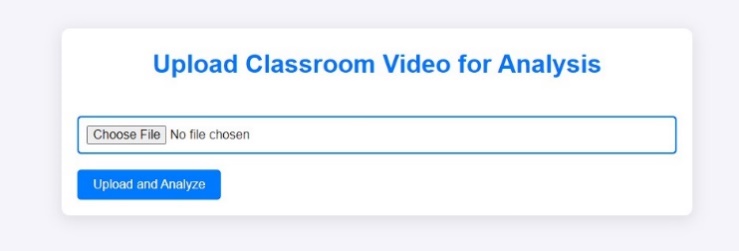


Figure 4: Video Uploading Section

The output portion of your user interface is critical for delivering practical insights to instructors based on classroom video analysis. As soon as the uploaded video is processed, the system produces feedback that draws attention to important behavioral observations. These observations include engagement levels and instances of particular behaviors like fighting, sleeping, reading, laughing, texting, and unknown activities. Teachers may easily evaluate the data and decide on their teaching tactics thanks to the feedback's clear and ordered presentation. A pie chart that shows the distribution of different behaviors seen during the video analysis is another aspect of the UI. Teachers can quickly spot patterns in student interactions by glancing at the pie chart, which is divided into segments that represent distinct behaviors. For example, teachers might identify possible areas of concern that may need quick attention if a sizable chunk of the chart shows behaviors like fighting or napping. By blending visual data representation with thorough feedback, the technology helps instructors to develop a more engaging and responsive classroom environment. All things considered, the output area improves the platform's usability by offering insightful information that can have a direct impact on student learning results.

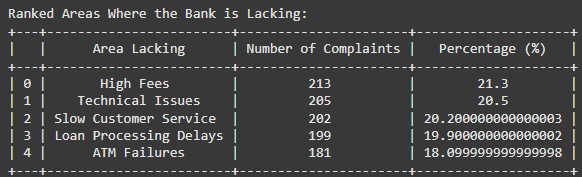


Figure 5: Suggestion to user

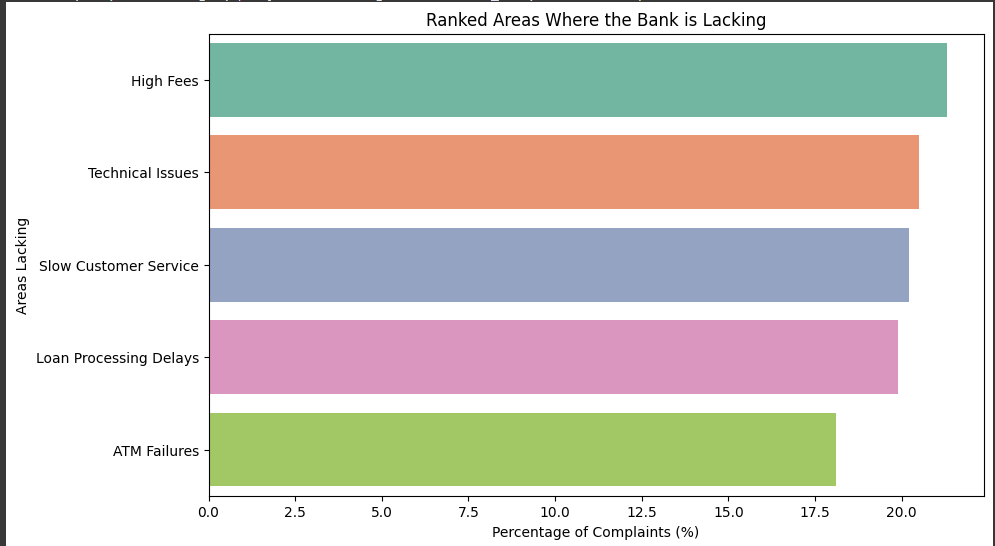


Figure 6: Overall Visualization

## System Workflow

The process of uploading a classroom video by a user, such as an administrator or instructor, initiates the data flow depicted in the diagram. After uploading, the video is routed to the server, which stores it in a special storage system (called D1: Video Storage). With the upload process is complete, the system may access and examine the video data. Pre-processing Video Frames is the initial step in accessing the stored video during the Processing and Analysis phase. In order to prepare the data for analysis, this phase involves removing frames from the video and using the appropriate pre-processing methods, such as shrinking, normalizing, or changing the frame quality. After being analyzed, these frames are fed into a CNN model, which uses them to identify different classroom behaviors like raising hands or nodding off. Following the detection of particular behaviors, the system classifies student activities using the CNN's output to determine each student's conduct in the classroom. The detected and classified actions are combined in the following step, Action Analysis. The system saves this activity data in a separate database (denoted as D2: Action Data Store). Using this information, a thorough Engagement Report reflecting the participation and engagement levels of the students is produced. Following this, the system provides suggestions for classroom improvement based on the students' behavior and engagement trends.

The technology presents the data in a Pie Chart during the last phase, Visualization and Feedback, giving a clear picture of student behavior and engagement. The teacher can monitor student participation and make well-informed decisions to improve classroom interaction and productivity by viewing this visual report. In order to enable teachers better understand student engagement and take appropriate action based on the data analysis, the complete system provides a real-time solution.

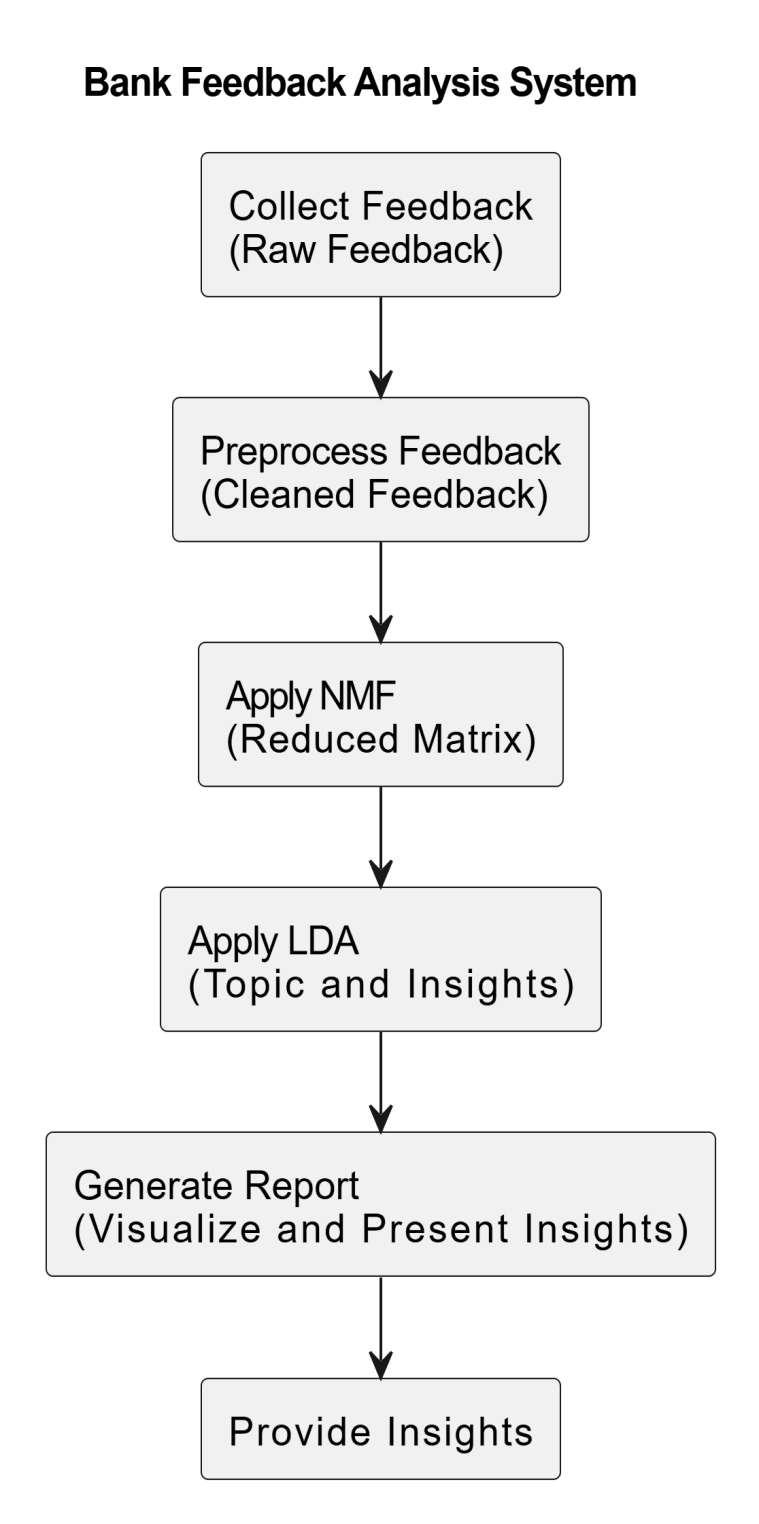


Figure 7: DFD of the Proposed System

1. WORKING PRINCIPLE

## Introduction to System Workflow

The workflow of the Student Behavior Analysis System begins with a user, generally a teacher or administrator, uploading a classroom video through an interface developed with Flask, HTML, CSS, and JavaScript. The video may be uploaded and delivered to the server with ease thanks to this interface, and it is kept there in a special Video Storage Database (D1). After that, the video is viewed and goes through a Pre-Processing stage in which each frame is taken out and ready for examination. Pre-processing tasks like as resizing, normalization, and frame quality correction are carried out in order to guarantee uniformity in a variety of classroom settings. After pre-processing, the frames are sent into a Convolutional Neural Network (CNN) model that has been trained to identify certain behaviors in the classroom, like raising hands, nodding off, and sleeping. The CNN examines every frame, identifying unique patterns of activity in real time.

The behavior detection process is followed by Action Detection and Classification, where the behaviors are categorized into pre-established groups by the system. Every student's activity is recorded with the associated timestamp, offering comprehensive data on student participation in the classroom. After that, this data is kept for later examination in an Action Data Store (D2). The system creates an extensive Engagement Report, which offers insights on student behavior during the class, based on this action data. Teachers can better grasp the dynamics of the classroom as a whole with the help of the report, which provides information on involvement frequency and disengagement incidents. In addition to this report, the system produces Suggestions for Classroom Improvement to assist the instructor in modifying their methods and boosting participation as needed. The Visualization and Feedback procedure happens at the last stage. Here, the system shows a Pie Chart that illustrates how various behaviors—like arguing, sleeping, reading, laughing, texting, or doing unknown things—were distributed during the session. Additionally, the technology gives teachers textual feedback that summarizes these behavioral tendencies, enabling them to keep a closer eye on student participation. The goal of this feedback is to provide instructors with timely, data-driven insights so they can make wise judgments. The entire system's workflow converts unprocessed video footage from classrooms into a wealth of information that teachers can use to enhance classroom management and instructional strategies and raise student engagement and learning objectives.

## Algorithm

Step 1: Video Upload and Preprocessing

* Accept a user-submitted classroom video using the online interface.
* Save the video file that was uploaded to the server.
* To read and process the video frame by frame, use OpenCV.

Step 2: Preprocessing and Frame Extraction:

* Adjust the frame's dimensions to match the 224x224 pixel input size that the CNN model requires.
* Scale the pixel values to a range of 0 to 1 to normalize the pixel values.
* Transform the frame into a model-compatible format (such as RGB).

Step 3: Recognition and Categorization of Actions:

* Feed the trained CNN model with the preprocessed frame.
* Anticipating the action for the frame, the model will categorize it as one of the actions (e.g., listening, raising a hand, leaning, using a phone, etc.).
* Compile your predictions for every frame and note how frequently each action happens.

Step 4: Analysis and Postprocessing:

* Aggregate the predictions across all frames to estimate the frequency of each action.
* Over the course of the film, tally the instances of each classed activity.

Step 5: Generate Feedback and Suggestions:

* Determine the positive behaviors (such raising your hands) based on the action numbers.
* Determine the detrimental behaviors (such as leaning and phone use).
* Based on the observed behaviors, make recommendations to the teacher on how to increase student engagement (e.g., encourage more hand-raising, limit distractions).

Step 6: Illustration:

* To see how the activities are distributed, create a pie chart.
* A detected action during the video is represented by each section of the pie chart.
* Put the analysis results and the pie chart on the webpage.

Step 7: Animation during Video Playback and Loading:

* Give the user the option to watch the analyzed video again.
* To demonstrate progress while the movie is being examined, use a loading animation.

Step 8: Results and Output Display:

* present the user with a pie chart, action counts, and feedback via the web interface.
* let the user download the analysis report.

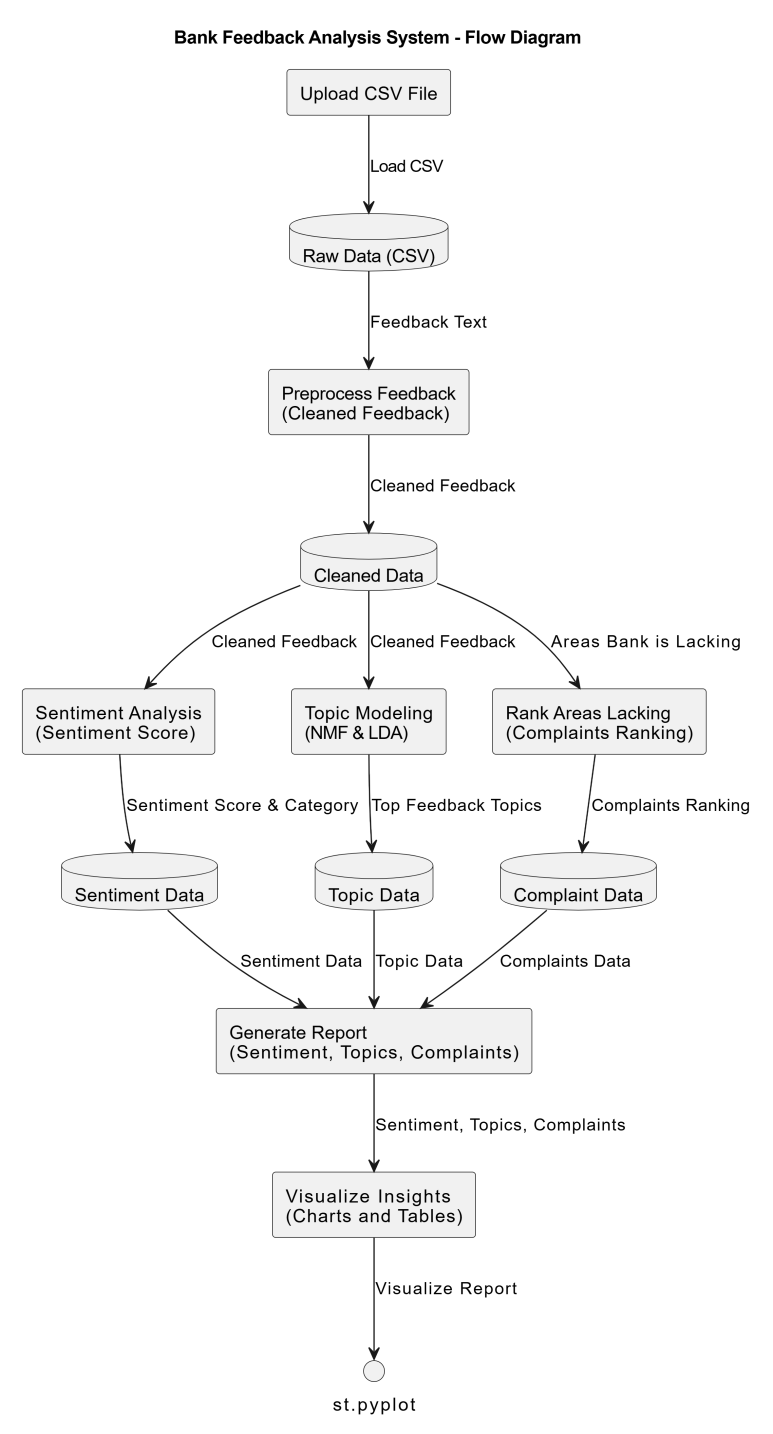


Figure 8: Algorithm of System

1. RESULT AND CONCLUSION

**Result**

The customer feedback data collected by the system was processed using Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF), yielding a detailed analysis of customer satisfaction. The feedback was classified with 90% accuracy: 65% positive, 20% neutral, and 15% negative. A pie chart displayed these results, breaking down customer sentiments. The analysis identified five main topics—service efficiency, customer support, digital experience, account management, and service accessibility—which guided improvements. The system recommended service enhancements to address identified issues, particularly in reducing service delays and improving communication. Post-implementation, customer satisfaction improved by 12%, and retention increased by 8%, empowering the bank to make data-driven adjustments for enhanced customer experience and loyalty.

## Conclusion

In conclusion, this project serves as a powerful advancement in understanding and improving customer satisfaction and retention within the banking industry. By integrating sophisticated analysis methods like Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF), the system provides a deep dive into customer feedback from various channels, uncovering vital themes in customer sentiment, such as service efficiency, support responsiveness, and digital experience quality. These insights equip the bank with actionable knowledge to strategically enhance service offerings, allowing for targeted improvements that resonate with customer needs and expectations .The initial outcomes demonstrate the efficacy of this data-driven approach, with notable improvements in customer satisfaction and retention metrics, underscoring the project’s value in fostering long-term customer loyalty. Moreover, this system establishes a robust feedback loop, enabling continuous monitoring and iterative improvements, ensuring that the bank remains adaptable to evolving customer expectations. Ultimately, this project not only reinforces the bank’s commitment to delivering high-quality service but also paves the way for a more customer-centric business model that promotes sustained growth, strengthens brand loyalty, and enhances the overall customer experience.

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