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BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

"Financial Risk Analysis using LLM"

By

Tasmiya Khan D17A 30

Purtee Mahajan D17A 39

Ketaki Nalawade D17A 44

Srushti Sambare D17A 54

Under the guidance of

Prof. Dr. (Mrs.) Sujata Khedkar

Department of Computer Engineering

Vivekanand Education Society's Institute of Technology

HAMC, Collector's Colony, Chembur,

Mumbai-400074

University of Mumbai

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1. Introduction

1.1 Introduction to the project

Earnings calls play an important role in boosting the investments in the company by conducting economic communication.Earnings conference calls follow the quarterly release of a firm's earnings, and have increased in popularity in recent years, mainly because of their ease of accessibility through modern communication mediums (e.g., applications like EarningsCast, interactive investor-relation websites). The purpose of these calls is to tell the market about the firm's future strategy and tactics, as well as to comment on the previous quarter's revenue streams and costs[1][2].

In an era marked by increasing economic globalization, businesses present tremendous opportunities to expand but also face increasing pressures from competitive markets [3]. As organizations seek to capture this environment actively, risk management and compliance have become key components of corporate governance, especially in financial services ensuring that companies can maintain trust and stability [4]. Today's complex corporate environment calls for a comprehensive risk management strategy to build organizational resilience and sustainability [5]. Financial pitfalls, in particular, are receiving accelerating engrossment due to their potentially eloquent impact on the organization's future. These risks can arise from a variety of sources, such as market fluctuations, regulatory changes, or faulty internal controls, making it necessary for companies to take a holistic approach to risk assessment and management [6]. The field of risk assessment and management has been
firmly established over the last 30–40 years, during which time it has evolved into an organized scientific discipline [7]. The decision-makers need to see beyond the risk evaluation; they need to combine the risk information they have received with information from other sources and on other topics [7].

The objective is to explore Large Language Models (LLMs) like Google's Gemini, which can enhance the risk assessment and management process by analyzing unstructured data from sources such as corporate earnings calls, annual public reports, and ESG reports. These insights, when combined, provide a solid foundation for more accurate and comprehensive risk assessments, ultimately contributing to better corporate decision-making.

1.2 Motivation for the project

Access to reliable and timely information is essential in the dynamic world of finance and investing. Earnings calls are a goldmine of complete data that investors, analysts, and decision-makers may use to make knowledgeable decisions. These conversations provide access to the inner workings of businesses and a window into their financial situation, business plans, and potential outcomes.

The requirement to effectively collect, analyze, and evaluate the content of earning calls is a problem in this flood of data, though. Earning calls may last for hours and are filled with technical terms, subtle terminology, and inconsistent audio quality. These calls can be difficult and time-consuming to listen to, transcribe, and understand.Timeline analysis for annual public reports ensures timely and accurate disclosures, enhancing transparency and building trust with stakeholders. Performing financial risk analysis is crucial for safeguarding assets, ensuring sustainable growth, and protecting against unforeseen market fluctuations. Thus , integrating transcription , transcript summarization , timeline analysis and financial risk analysis all at one place was another problem which was important to be addressed.

These problems served as our inspiration for starting the "Financial Risk Analysis using LLM" project. We understood how much this process might be streamlined by using cutting-edge technologies. Our goal is to completely transform the way earning calls and annual public reports are assessed by leveraging the power of LLMs.

1.3 Drawback of the existing system

Using LLMs can result in incorrect or "hallucinated" responses, potentially misleading users and affecting financial decisions.Reliance on outdated training data limits their ability to provide relevant, real-time market analysis.[8]

GPT-4 tends to assign equal importance to all features, potentially misrepresenting variable significance in credit risk assessments. Although its reports have fewer errors, the risk of generating inaccurate information remains a concern with LLMs.[9]

A major drawback is the challenge of integrating natural language data with structured graph data, as the model's effectiveness heavily relies on the quality of the financial knowledge graphs (KGs).[10]

A key drawback is the significant effort required for data annotation, especially with unannotated news data, as the model focuses mainly on event prediction rather than providing a comprehensive credit assessment.[11]

The model is limited to US companies from 2018-2020 and may carry biases due to the specific news sources used in dataset creation.[12]

ChatGraph has limitations in supporting certain graph types or complex structures, depends on the quality of integrated APIs, and requires users to have a basic understanding of graph concepts.[13]

Early classification models relied on fixed output vocabularies, leading to out-of-vocabulary (OOV) issues that limit their ability to handle unseen terms.[14]

The performance of the models is closely tied to the dataset quality, with accuracy dependent on effective visual feature extraction from chart images, while they may struggle with new or unseen chart types and styles.[15]

Empirical prompt creation may overlook reasoning complexities, and reliance on table versions of charts could restrict the overall quality of the model.[16]

It faces accuracy issues, algorithmic biases, depends on audio quality, lacks contextual understanding, and raises data security concerns.[17]

Manual transcription is time-consuming, professional services can be costly, and software programs may lack accuracy and customization.[18]

1.4 Problem Definition

It has become crucial to analyze business earnings calls and annual public reports because it is challenging to get highly accurate and efficient results all in one location when using traditional methods of analysis. Earnings calls last for a long duration. Understanding and remembering all the crucial information becomes a tedious job. This causes information overloading. Some information might be overwhelming especially for an investor who is new to the company or the industry. It takes a lot of time to study such a large text, even if a transcript of the call is available. It is observed that investors are more devoted and fond of finicky types of investment choice and preferences[29]. The 'disclosure bias' is another major issue. Some businesses may emphasize just the positive aspects while downplaying the unfavorable information. As a result, investors may struggle to gain a clear image of the company. These changes can be costly to investors, resulting in greater trading fees, missed purchasing opportunities, or overall position losses[1].During the earnings calls, some analysts often ask questions that would promote their own investment opinions. This may influence the investors and also give biased information regarding the company.

The complexity and length of reports can overwhelm investors, particularly those who are new to the company or industry, leading to information overload and delayed decision-making.Thus , a chatbot which could answer the required questions related to the report helps in saving time and energy.

Traditional approaches to financial risk analysis rely heavily on structured data and static models, making it difficult to capture the dynamic nature of financial markets, which are influenced by unstructured data such as earnings call transcripts, news, and public reports. These methods often fail to account for biased or selective disclosures by companies, leading to incomplete or skewed risk assessments.The objective is to integrate LLMs into financial risk analysis to address these limitations. By processing unstructured data, such as earnings call transcripts, annual reports, news articles, and analyst opinions, LLMs can extract relevant risk indicators, identify potential biases in company disclosures, and provide a more holistic risk profile.

1.5 Relevance of the Project

The relevance of this project stems from its potential to significantly enhance the financial analysis process for investors and stakeholders by streamlining the traditionally cumbersome methods of interpreting earnings calls and public reports. Earnings call transcription automates the conversion of spoken content into text, enabling investors to quickly access key discussions without needing to sit through lengthy calls.Transcript summarization further condenses the information, allowing users to extract the most critical details in a concise format, saving time while maintaining a clear understanding of a company's performance and strategies.

The timeline analysis module is highly beneficial in identifying trends and pinpointing significant events or shifts in a company's operations or financial health over time, helping stakeholders to contextualize performance and predict future movements. The annual public report chatbot offers an interactive way for investors to quickly retrieve relevant sections of the report, ask specific questions, and get immediate, clear responses. The risk analysis feature enables a comprehensive assessment of potential financial risks, ensuring that investors are aware of red flags that may not be obvious through traditional reading. Finally, chat with graphs of the report integrates data visualization, allowing users to explore key metrics and trends graphically, making complex data easier to digest and interpret. All the modules of the project provide a holistic, efficient, and investor-friendly approach to financial analysis, facilitating more informed decision-making and making it highly relevant in the finance industry.

1.6 Methodology used

Transcript Generation : Assembly AI is used which converts earnings call audio into accurate, structured text for easy access to all spoken content.

Transcript Summarization : BART(Bidirectional and Auto-Regressive Transformers) model to generate coherent and concise summaries of earnings call transcripts, capturing the most important points with contextual understanding.

Timeline Analysis : It uses spacy to extract the past , present and future sentences mentioned in the earnings call.

Financial Risk Analysis : Chatbot is made using Gemini and streamlit which generates FAQs when the report is uploaded.

2. Literature Survey

2.1 Research Papers

Title of Paper	Journal	Year	Methodology Used	Merits
RiskLabs: Predicting Financial Risk Using Large Language Model Based on Multi-Sources Data [8]	eprint arXiv:2404.07452	April 2024	RiskLab framework comprises four main modules: 1) Earnings Conference Call Encoder; 2) Time-Series Encoder; 3) Relevant News Encoder; and 4) Multi-Task Prediction Block. It combines self-attention, Bayes-VaR forecasting, and dynamic time windows with news filtering and contextual compression for flexible training.	It integrates diverse information sources for a holistic market view and enables multi-task predictions, offering investors nuanced insights.
Enhancing Credit Risk Reports Generation using LLMs: An Integration of Bayesian Networks and Labeled Guide Prompting [9]	Conference: ICAIF '23: 4th ACM International Conference on AI in Finance	November 2023	A novel prompt engineering technique designed to enhance the quality of responses from GPT-4 by ensuring it addresses specific aspects of credit risk analysis.	The application of LGP and Bayesian networks led to the generation of high-quality credit risk reports that were statistically preferred by evaluators over traditional human-generated reports. The use of LLMs like GPT-4 can increase the efficiency and scalability of credit risk assessments.
Fusing LLMs and KGs for	eprint arXiv:2407.17190	July 2024	Risk Contagion Causal Reasoning Model is	The model helps uncover the reasons

Formal Causal Reasoning behind Financial Risk Contagion [10]			used to understand how financial risks spread. Financial Knowledge Graphs (KGs) provide important information to help LLMs reason about risks. Fusion Module helps combine information from LLMs and KGs effectively. Uses Sankey diagrams to show how risks spread and their intensity.	behind how risks spread. Identifying risk pathways can lead to better strategies to prevent financial crises.
Identifying Corporate Credit Risk Sentiments from Financial News[11]	NAACL-HLT 2022: Industry Track Papers.	2022	Credit Relevance model - used to filter out irrelevant news articles that do not pertain to credit risk Targeted entity sentiment Model - It classifies the sentiment of each entity as Positive, Negative, or Neutral based on the context in which they are mentioned Risk Categorization Model - categorizes sentences or paragraphs into specific risk categories related to credit events. Custom scoring mechanism (Credit Sentiment Score - CSS)	Automates the analysis of financial news Provides insights into credit risk Effectively distinguishes between defaulters (companies that have experienced severe credit events) and non-defaulters (companies that have not)
Predicting Companies' ESG Ratings from News Articles Using Multivariate Time Series Analysis.[12]	arXiv:2212.11765 [q-fin.GN]	2023	Multivariate time series analysis Sentiment analysis Semantic and topic analysis CNN and transformer-based models	Creation of a large and diverse ESG-related news dataset Accurate predictions of ESG ratings Comprehensive analysis of model capabilities

ChatGraph: Chat with Your Graphs[13]	arXiv, 2024. [Online]. Available: https://arxiv.org/abs/2401.12672v1	2024	The ChatGraph methodology combines API retrieval, graph-aware LLM, and fine tuning modules to generate API chains for graph analysis from natural language input, enhancing user interaction with graphs.	ChatGraph simplifies graph analysis by enabling natural language interactions and integrates advanced modules like API retrieval and graph-aware LLMs for diverse real-world applications.
From Pixels to Insights: A Survey on Automatic Chart Understanding in the Era of Large Foundation Models[14]	arXiv preprint arXiv:2403.12027 (2024).	2024	The methodology for automatic chart understanding encompasses several key components aimed at enhancing the interpretation of charts. It begins with classification-based models that leverage visual and textual features, often using CNNs for chart encoding and LSTMs for question processing	Chart-to-Table Conversion: Extracts structured data from visual representations for better analysis. Classification-based Models: Utilize visual and textual features, often employing CNNs for chart encoding and LSTMs for question encoding
ChartQA: A Benchmark for Question Answering about Charts with Visual and Logical Reasoning[15]	arXiv preprint arXiv:2203.10244.	2022	The study uses a dataset of 9.6K human-written and 23.1K generated questions, with ChartOCR and neural models to extract data and visual features from charts. Transformer models like T5 and VL-T5 process and integrate this information, are trained for accuracy, and evaluated for performance improvement.	**Complex Reasoning**: Handles complex questions needing logical and arithmetic operations. **Data Integration**: Combines visual and tabular data for better chart understanding. **Human-Centric Design**: Reflects natural language and practical question types.
Chart-based Reasoning: Transferring	eprint arXiv:2403.12596	March 2024	The study enhances core image representations to	Synthetic data generation creates diverse training

Capabilities from LLMs to VLMs [16]			improve reasoning in VLMs. Fine-tuning is done using synthetic datasets with reasoning traces from advanced LLMs. The hybrid online setup refines numerical reasoning, and the methods are evaluated on the ChartQA benchmark for visual question answering on charts.	examples, improving model robustness. This approach transfers reasoning from larger LLMs to smaller VLMs, boosting performance with minimal computational resources.
Transcribing in the digital age: qualitative research practice utilizing intelligent speech recognition technology[17]	European Journal of Cardiovascular Nursing, Volume 23, Issue 5, Pages 553–560	July 2024	The study employed intelligent speech recognition within Microsoft Teams for simultaneous transcription, algorithmic processing, accuracy checking, and secure data management to enhance transcription efficiency and accuracy.	Speech recognition technology enhances efficiency, cost savings, data immersion, reduces manual effort, and improves accessibility.
From voice to ink (Vink): development and assessment of an automated, free-of charge transcription tool[18]	BMC Research Notes, vol. 17, no. 95	2024	The transcription methodology includes manual transcription, professional services, and software-based programs, each offering trade-offs in time efficiency, data quality, and potential researcher bias.	Manual transcription ensures deep engagement with data, professional services save time, and software programs offer speed and cost-effectiveness.
Automatic speech recognition and the transcription of indistinct forensic audio: how do the new generation of systems	Frontiers in Communication. 9. 1-9. 10.3389/fcomm.2024.1281407/full.	2024	The study compared the accuracy of 12 ASR systems, including Whisper, Descript, and Sonix, against human transcribers on forensic-like audio, focusing on word error rates and audio quality.	The study offers a thorough comparison of ASR systems, highlighting Whisper's accuracy and relevance to forensic applications.

fare?[19]				
Transcription and Qualitative Methods: Implications for Third Sector Research[20]	Voluntas 34, 140–153	2023	The study analyzed 212 qualitative research articles to examine how transcription is discussed, finding that 41% omitted it, while others varied in detail, highlighting the impact of theoretical background on transcription style choices.	The study underscores the need for detailed reporting and an interpretivist approach to transcription in qualitative research.
Advanced Search and Summarization of Educational Documents Using Machine Learning [21]	Journal of Nonlinear Analysis and Optimization Vol. 15, Issue. 1, No.6 : 2024 ISSN : 1906-9685	2024	The study focuses on fine-tuning language models to better extract key information from various texts, particularly in the fields of science and literature.	The methodology uses embeddings to capture semantic meaning, which helps in generating contextually rich summaries. Advanced pre-trained LLM (Flan-T5, BART) provides high-quality summarization.
LaMSUM: A Novel Framework for Extractive Summarization of User Generated Content using LLMs [22]	Arxiv. Computation and Language (cs.CL); Machine Learning (cs.LG)	2024	This innovative work introduces LaMSUM, a framework that harnesses the power of LLMs to create extractive summaries from user-generated content.	This addresses the challenge of summarizing extensive content that exceeds the context window of LLMs by employing a multi-level summarization approach.
A Comprehensive Survey on Process-Oriented Automatic Text Summarization with Exploration of LLM-Based Methods [23]	Arxiv Artificial Intelligence (cs.AI)	2024	This study delves into the significance of ATS in reducing human effort in processing large texts, while also addressing the practical applications of these methods in real-world scenarios. It highlights the evolution of ATS techniques, particularly in light of the transformative impact of Large Language	The introduction of a "Process-Oriented Schema" offers a structured and practical framework for understanding ATS, aligning theoretical concepts with real-world implementations.

			Models (LLMs).	
Mining Both Commonality and Specificity From Multiple Documents for MultiDocument Summarization [24]	IEEE Access (Volume: 12)	2023	This study presents an innovative method that balances the need for coverage and content diversity by utilizing a class tree derived from hierarchical clustering of documents. By selecting sentences based on their relevance to both common themes and unique specifics, this approach ensures that summaries are both informative and varied. .	The method captures the overall common information across all documents while also highlighting the unique characteristics of different subclasses.
From Moments to Milestones: Incremental Timeline Summarization Leveraging Large Language Model [25]	Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)	2024	1.LLM-TLS approach collects and preprocesses text data, detects events using large language models (LLMs), clusters similar events, and constructs a dynamic timeline, updating it in real-time. 2. Summarizes the clustered events, evaluates performance using metrics like precision and ROUGE, and refines the process iteratively based on comparative analysis with baseline models.	1.Offers real-time, scalable timeline construction with dynamic event clustering, 2.Effectively handles noisy and large data streams 3. Generates high-quality abstractive summaries
Temporal analysis of topic modeling output by machine learning techniques[26]	International Journal of Data Science and Analytics	2024	Data is collected, preprocessed, and topics are modeled using LDA/NMF, with trends tracked through feature vectors. Dimensionality	Flexibility, applicability, various datasets. Robust evaluation, validation. Dynamic Topic Analysis

			reduction and clustering identify patterns, which are evaluated, visualized, and interpreted for reporting.	
Noun and Verb Phrase Extraction in Natural Language Processing: A Comparative Study of Approaches[27]	Procedia Computer Science Volume 235 , 2024, Pages 2876-2885	2024	Preprocessing text (tokenization, stemming) using POS tagging with models to label nouns and verbs, incorporating rule-based, statistical, and machine learning techniques (SpaCy, NLTK) for extraction. Performance evaluation shows high accuracy (SpaCy 95%, POS tagging 96%)	1. High accuracy: 96% POS tagging, 95% SpaCy. 2. Versatile, adaptable across domains/languages 3. User-friendly
Visualizing Parts of Speech Tags by Analyzing English Language Text [28]	IEEE	2024	CRFs and Spacy Integration Evaluates CRFs with Spacy against traditional methods, showing superior tagging accuracy. Includes graphical or annotated text to visualize POS tags	Accuracy: Combines CRFs and Spacy for better POS tagging accuracy. Real-time Processing, Improved Interpretability. Easily scalable and adaptable.

Table 1. Literature Review

2.2 Interaction with domain experts

Interacting with domain experts is crucial for the success of the project, as their insights can significantly enhance the accuracy and relevance of the financial analysis modules. By collaborating with financial analysts, data scientists, and industry professionals, the project team can gain a deeper understanding of the key metrics, terminology, and nuances specific to earnings calls and annual public reports. This interaction can help refine the data annotation process, ensuring that the information captured is not only comprehensive but also contextually appropriate.Experts can provide valuable feedback on the summarization outputs and risk analysis, ensuring that the results align with real-world expectations and enhance decision-making for investors and stakeholders. Engaging with domain experts also fosters a

collaborative environment that encourages continuous improvement, helping to identify potential challenges and opportunities for further development within the project.

3. Requirement of Proposed System

3.1 Functional Requirements

1. **Data Upload & Processing**:
    a. Allow users to upload corporate earnings call audio, YouTube video URLs, transcripts in PDF format, and financial reports.
    b. Extract audio from video URLs and perform speech-to-text to generate a transcript.
    c. Generate a summary and perform timeline analysis on the earnings call transcript.
    d. Perform tone and semantic analysis on earnings call transcripts for risk analysis.
    e. Implement argument mining to extract key points and assess risks from the transcripts and news.
    f. Integrate a search bar to fetch company financial reports based on company name and year.
    g. Extract relevant company news articles based on the provided timeframe.
    h. Combine data from earnings calls, transcripts, company news, and financial reports to generate a comprehensive risk report.
2. **Risk Report Generation**:
    a. Perform a detailed risk analysis based on financial performance metrics, corporate strategy, governance, capital allocation, market focus, ESG, and forward-looking statements.
    b. Provide users the ability to download the final risk report in PDF format.
3. **Graph Interpretation**:
    a. Dynamically generate and interpret visual financial data, including charts and graphs, with an emphasis on identifying potential risks or insights.
4. **Data Validation**:
    a. Ensure uploaded data belongs to the surrounding relevant timeframe, such as matching earnings call quarters with financial report years and news periods.

3.2 Non-Functional Requirements

1. **Performance**:
    a. System should process uploaded audio, video URLs, and PDF transcripts efficiently with minimal latency.
    b. Real-time risk analysis and report generation should be optimized for fast turnaround.
2. **Scalability**:
    a. The system should scale to handle multiple users concurrently uploading and analyzing large datasets, ensuring high availability during peak loads.
3. **Accuracy**:
    a. The tone, semantic analysis, argument mining, and risk assessment algorithms should be highly accurate and robust to ensure reliable decision-making for investors.
4. **Security**:
    a. Ensure that all uploaded data is securely stored and processed.
    b. Implement access controls, encryption, and secure data transmission.
5. **User Experience**:
    a. The system should have an intuitive interface that allows users to easily upload files, analyze data, and download reports.
    b. Provide clear instructions and feedback during the process, with visual aids for graph interpretation.
6. **Compatibility**:
    a. Support for multiple formats, including audio, video URL, PDF, and different financial report formats, ensuring compatibility with a wide range of data sources.

3.3 Constraints

1. **Data Dependency**:
    a. The system is reliant on the availability of corporate earnings calls, financial reports, and news articles from third-party sources (company websites, YouTube, and news outlets).
2. **Time Frame Alignment**:
    a. Data sources must align in terms of the timeframe (e.g., earnings calls, financial reports, and news must be from the same quarter or year), which imposes constraints on the processing of mismatched data.
3. **Processing Power**:
    a. High computational resources may be required for processing audio, video, large transcripts, and conducting detailed risk analysis.
4. **Legal and Compliance**:
    a. The system must comply with legal regulations regarding data usage and storage, especially when handling financial information and corporate documents.
5. **Data Quality**:

a. The accuracy of the analysis is highly dependent on the quality of the uploaded audio, transcript, and financial reports. Poor data quality could negatively impact risk assessments.

3.4 Hardware & Software Requirements

1. **Frontend:**
   The frontend will be done using React.js - a JavaScript Frontend Framework which will provide a user interface for our project.

2. **Transcribing the source earning call:**
   Google Text-to-Speech: We have used Assembly AI tool to transcribe the uploaded source file.

3. **Summarization of transcript:**
   We will use argument mining to extract and summarize key arguments from the transcribed text. This method identifies core arguments and supporting evidence. Advanced models like BERT or Gemini will be employed to enhance the summarization, with BERT providing bidirectional context and Gemini offering deeper argument analysis. This approach ensures a focused and insightful summary of complex discussions.

4. **Extracting Financial Data:**
   NLP Model and Named Entity Recognition (NER): For the extraction of financial data from our transcripts, we will require NER techniques. The pre-trained model can be used which has NER techniques, but it should be trained specifically for the extraction of financial data. We need to train the model for extracting quantitative measures, keywords related to revenue, earnings per share, revenue generated by the company and a lot more related parameters. This model will identify all the texts that match financial measures and parameters from the generated transcripts.

5. **Data interpretation of charts :** Users can chat with charts or graphs, which the Gemini model will analyze to extract meaningful insights and trends, enabling a deeper understanding of complex data and supporting informed decision-making.

6. **Risk assessment and Investment prediction:** Using either the Gemini or PaLM model, we will analyze argumentative structures in financial reports, news to assess risks and predict investment outcomes, helping users make more informed decisions based on market insights.

7. **News as input :** Integrate media news using a news API to evaluate the current economic, political, and social climate impacting market sentiment and investor behavior. This helps gauge how events and trends influence market dynamics and investment decisions.

8. **Financial Report Retrieval and Risk Analysis**: A search bar will be available for users to input a company name and year, allowing them to fetch and download the company's financial reports using the Google Custom Search API. Once the reports are uploaded, the system will provide a risk analysis, offering insights into potential financial risks. This feature streamlines the process of accessing and evaluating financial data, supporting informed decision-making and thorough risk assessment.

3.5 Techniques utilized till date for the proposed system

1. **Earnings Call Transcription**:
    a. Utilized **Assembly AI** for automatic transcription of earnings calls.
2. **Summarization of Transcripts**:
    a. Applied **Argument Mining** to extract key arguments and summarize content from the transcripts, identifying core arguments and supporting evidence.
    b. Employed **BERT** (Bidirectional Encoder Representations from Transformers) and **Gemini** models for deeper, context-aware summarization.
3. **Natural Language Processing (NLP) and Named Entity Recognition (NER)**:
    a. Used **NLP and NER** techniques to extract financial data such as revenue, earnings per share, and other quantitative metrics from the transcribed earnings calls.
    b. Trained an NER model specifically for extracting financial entities and metrics from corporate data.

3.6 Tools utilized till date for the proposed system

1. **Assembly AI**:
    a. Used for automatic transcription of earnings call audio files, converting them into text for further processing.
2. **BERT (Bidirectional Encoder Representations from Transformers)**:
    a. Employed for bidirectional context-aware analysis during summarization and argument mining in earnings call transcripts.
3. **Gemini Model**:
    a. Utilized for summarization, argument mining, chart interpretation, and risk assessment. It provides deeper argument analysis and trend extraction.
4. **Google Custom Search API**:
    a. Integrated to enable users to search for and retrieve financial reports based on company name and year.
5. **PaLM Model**:

a. Used for analyzing structures in financial reports and news to perform risk assessments and predict investment outcomes.

3.7 Project Proposal

The proposed system - 'Fincalls - Risk Analyzer' acts as an effective solution for the economic development of the company as well as provide an ease of analysis to the investors.

Following sources of components:

1. Corporate Earnings Calls Analyzer
    a. The corporate earnings call audio is available on the company websites. It can be uploaded. The tone and semantic analysis of the call will be done and a risk analysis will be given.
    b. Earnings call audio, YouTube videos, and transcripts are automatically transcribed and summarized using AI-powered tools.
    c. The summarization process focuses on extracting key arguments and core insights from lengthy transcripts, ensuring an accurate and concise overview.
2. News and Financial Report Integration
    a. The system fetches relevant financial reports and news articles via APIs, ensuring up-to-date information for risk analysis.
    b. Users can input a company name and year to retrieve financial reports and gain insights through automatic risk assessment tools.
3. Risk Assessment and Investment Prediction:
    a. The system combines financial data, earnings call analysis, and news sentiment to generate risk assessments and predict investment outcomes.
    b. This helps investors understand the potential risks and rewards associated with particular companies.
4. Chart and Graph Interpretation
    a. Generated financial charts can be analyzed to identify trends and insights, will help investors to make effective decisions.

4. Proposed Design

4.1 Block diagram representation of the proposed system

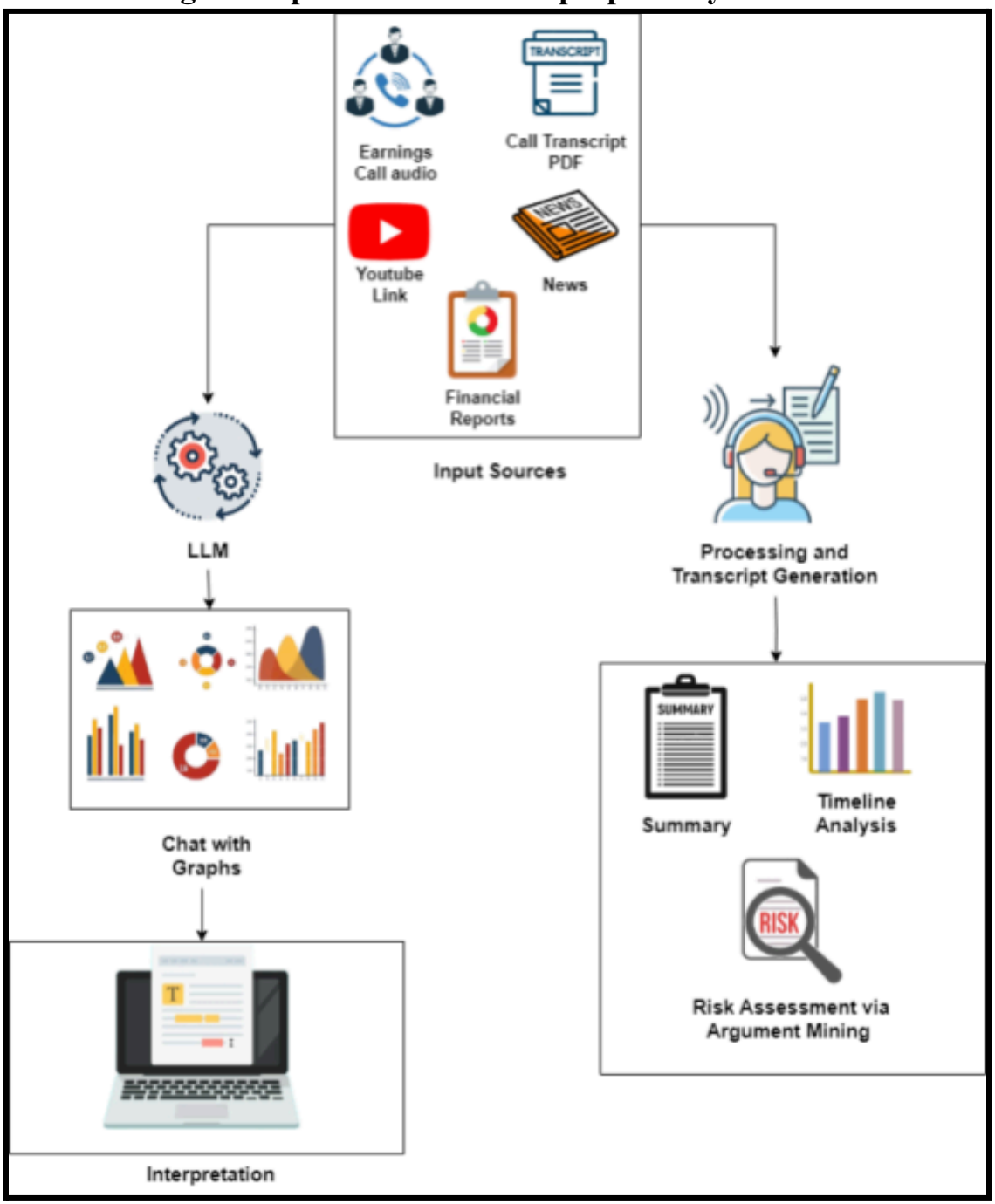


Fig. 1 Block diagram of the proposed system

This will be the whole block diagram of what the user can give as input to the system and what he will get as output.

The proposed system - ‘Fincalls - Risk Analyzer’ acts as an effective solution for the economic development of the company as well as provide an ease of analysis to the investors.

Following sources of data are taken into consideration.

1. Corporate Earnings Calls Audio
    a. The corporate earnings call audio is available on the company websites. It can be uploaded. The tone and semantic analysis of the call will be done and a risk analysis will be given.
    b. Also, a transcript of the call will be generated.
    c. Using this generated transcript, the summary of the call as well as the timeline analysis of the call will be given.
2. Corporate Earnings Calls Youtube Video URL
    a. Along with the youtube channels owned by the companies, there are multiple channels that post earnings calls video recordings on youtube.
    b. Again, after extracting the audio, the tone and semantic analysis of the call will be done and a risk analysis will be given.
    c. Using this generated transcript, the summary of the call as well as the timeline analysis of the call will be given.
3. Corporate Earnings Calls Transcript PDF
    a. Sometimes, even the direct transcript is available instead of the call.
    b. From this transcript, the summary of the call as well as the timeline analysis of the call will be given.
    c. Also, via argument mining, the risk analysis will be given.
4. Company News
    a. The company name and the duration of the release of the news articles will be given.
    b. And from this, the relevant news will be extracted.
    c. A risk analysis will be given corresponding to the extracted news.
5. Financial Report
    a. A search bar will be provided, where, after giving the company name and the year as an input, the financial reports of the company will be fetched.
    b. They can be downloaded and used further.
    c. Once uploaded, a risk analysis of the reports will be provided, too.

    Note that, the uploaded data should belong to surrounding durations. That is, the quarter to which the earnings call belongs should be a part of the year to which the financial report belongs. Also, the news duration should lie in the same duration.

Now, the risk analysis from all the above mentioned sources will be combined to form a Risk Report. This report can be downloaded in a PDF format.

The Risk Report will be created based on the following aspects:

1. Financial Performance Metrics: To analyze metrics focusing on revenue growth, profitability, cash flow, and debt levels and identify any potential risks associated.
2. Corporate Strategy and Governance: Review recent changes in leadership or corporate structure to identify potential risks associated with these changes.
3. Capital Allocation and Dividends: It looks at the company's strategies for reinvesting profits, paying dividends, conducting share buybacks, and managing debt.
4. Product and Market Focus: Evaluate how well the company's products and market strategy align with current and future market trends.
5. ESG and Social Impact: Examine the company's ESG reports, CSR initiatives, and sustainability goals to identify any gaps or areas where the company is underperforming.
6. Forward-Looking Statements and Guidance: Identify the company's future expectations by reviewing management's guidance on growth prospects, potential risks, and strategic priorities highlighted during the earnings call.

Another part is that the interpretation of dynamically generated graphs will also be given.

4.2 Modular diagram representation of the proposed system

a. Earnings Call Analysis

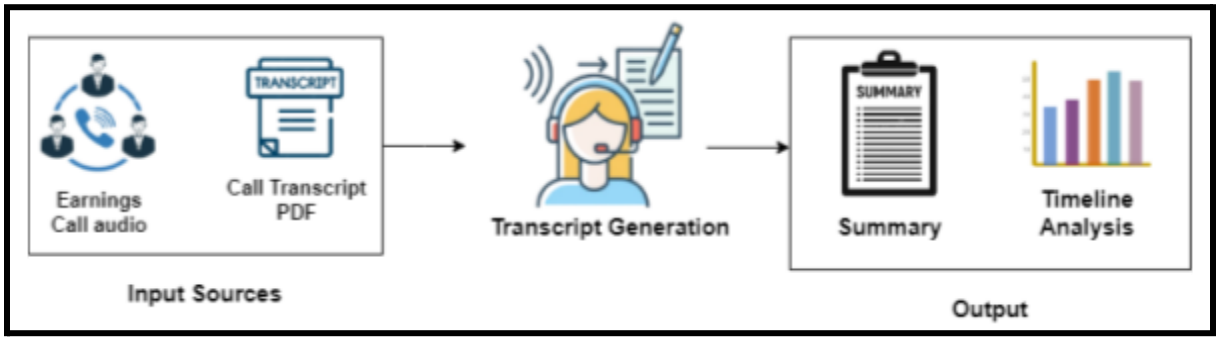


Fig. 2 Modular Diagram - Earnings Call Analysis

The modular diagram of the two kinds of input the user can upload and the output of transcript, summary and timeline analysis he will get.

b. Risk Assessment

Fig. 3 Modular Diagram - Risk Assessment

The modular diagram of different inputs the user will feed the system and the many outputs he will get for risk assessment.

The user will have to upload either or all of the supported input sources which comprise of the Earnings Call audio, Earnings Call Transcript, Earnings Call YouTube Video URL, News and financial reports. Then, the user can either go for 'Chat with Graphs' or 'Risk Analysis' module.

If the user chooses the former, then, the numerical and the statistical data would be extracted from the given sources and would be represented in a graphical format. The interpretation of the formed graphs will be given and the user can interact and chat with those visualisations.

However, if the user chooses the latter, then, a separate risk analysis will be done on each source and the combined results will be used to form a risk report. Along with that, some other features include summary and timeline analysis of the Earnings Call.

4.3 Design of the proposed system

a. Data Flow Diagrams

1. Transcription Module

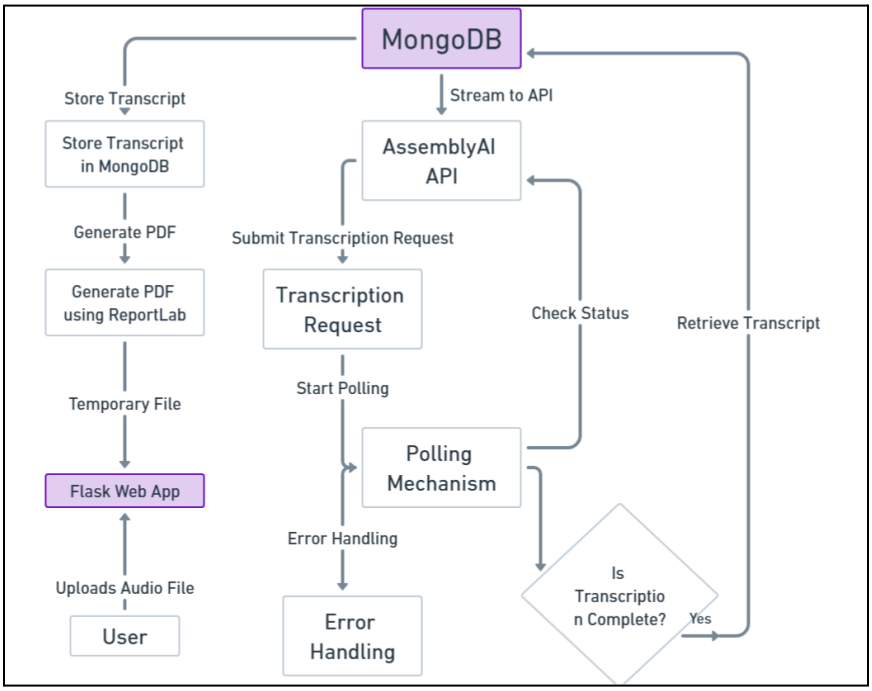


Fig. 4.3.a.1. Transcription Data flow diagram

The transcription module begins with a user uploading an audio file via the Flask web app, which is then sent to AssemblyAI for transcription. The completed transcription is stored in MongoDB, converted to a PDF, and returned to the user.

2. Summarization

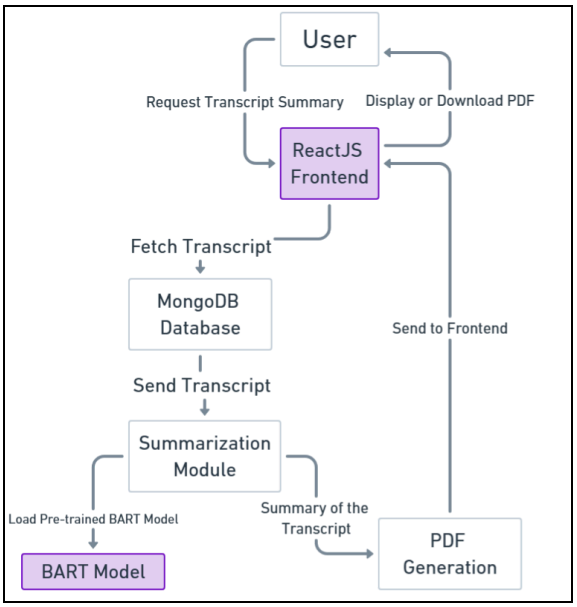


Fig. 4.3.a.2. Summarization Data flow diagram

The summarization process begins with a ReactJS frontend requesting a transcript from MongoDB. The transcript is summarized using a BART model, then converted to a PDF, and displayed or made available for download to the user.

3. Timeline Analysis Module

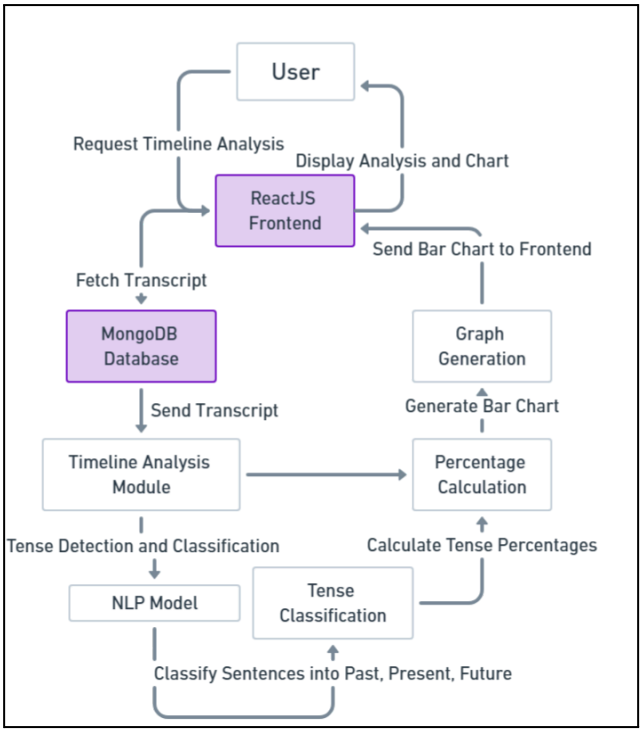
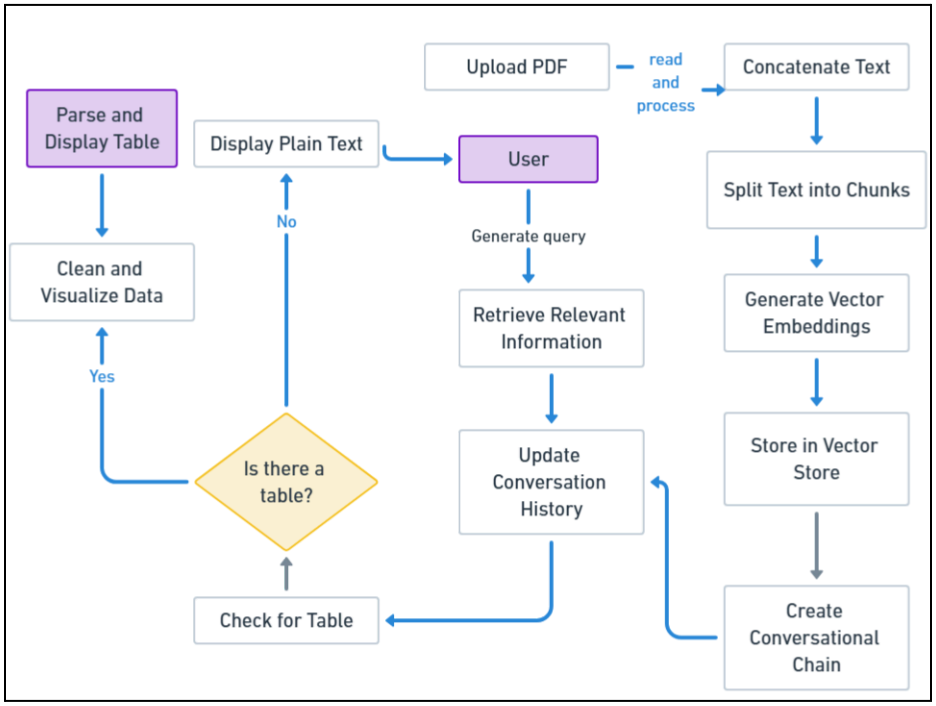


Fig. 4.3.a.3. Timeline Analysis Data flow diagram

The timeline analysis system fetches a transcript from MongoDB via the ReactJS frontend, processes it with an NLP model for tense detection, and categorizes sentences into past, present, or future. The results are visualized as a bar chart and displayed on the frontend.

4. Risk Assessment Module



The Risk Assessment Module begins with financial data being uploaded and preprocessed to extract key information.

b. Flowchart for the proposed system

i. Transcript Generation

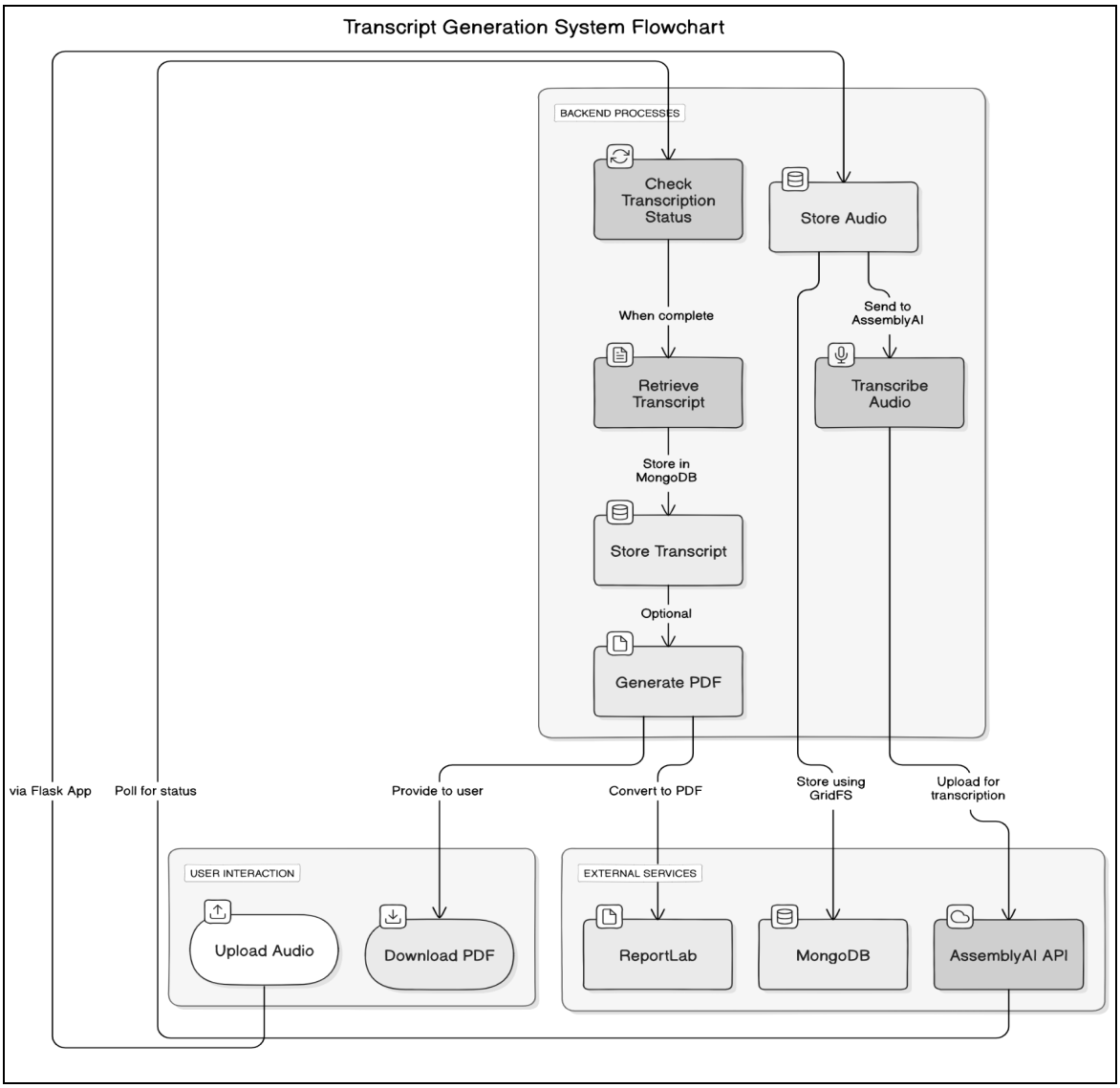


Fig. 4.3.b.1. Flowchart of Transcript Generation

The flowchart depicts the transcript generation system's process. Users upload audio files, which are stored using GridFS and sent to the AssemblyAI API for transcription. The system monitors the transcription status and retrieves the transcript upon completion. The retrieved transcript is stored in a MongoDB database, and an optional step allows the generation of a PDF using ReportLab. Users can then download the PDF. The system operates via a Flask app, handling user interactions and polling for transcription status updates. External services, including MongoDB, ReportLab, and AssemblyAI, are integrated into the process.

ii. Transcript Summarization

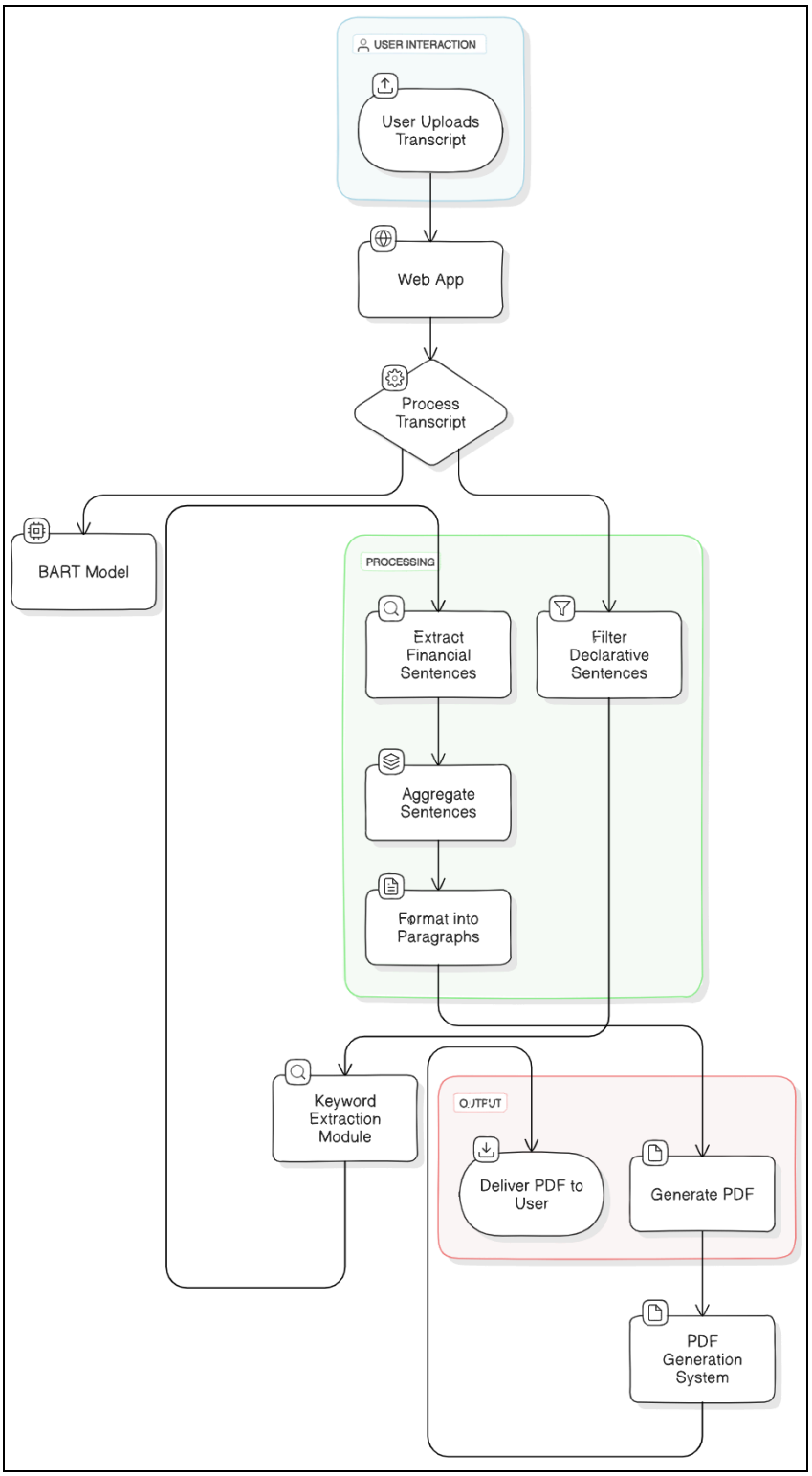


Fig. 4.3.b.2. Flowchart of Transcript Summarization

iii. Timeline Analysis

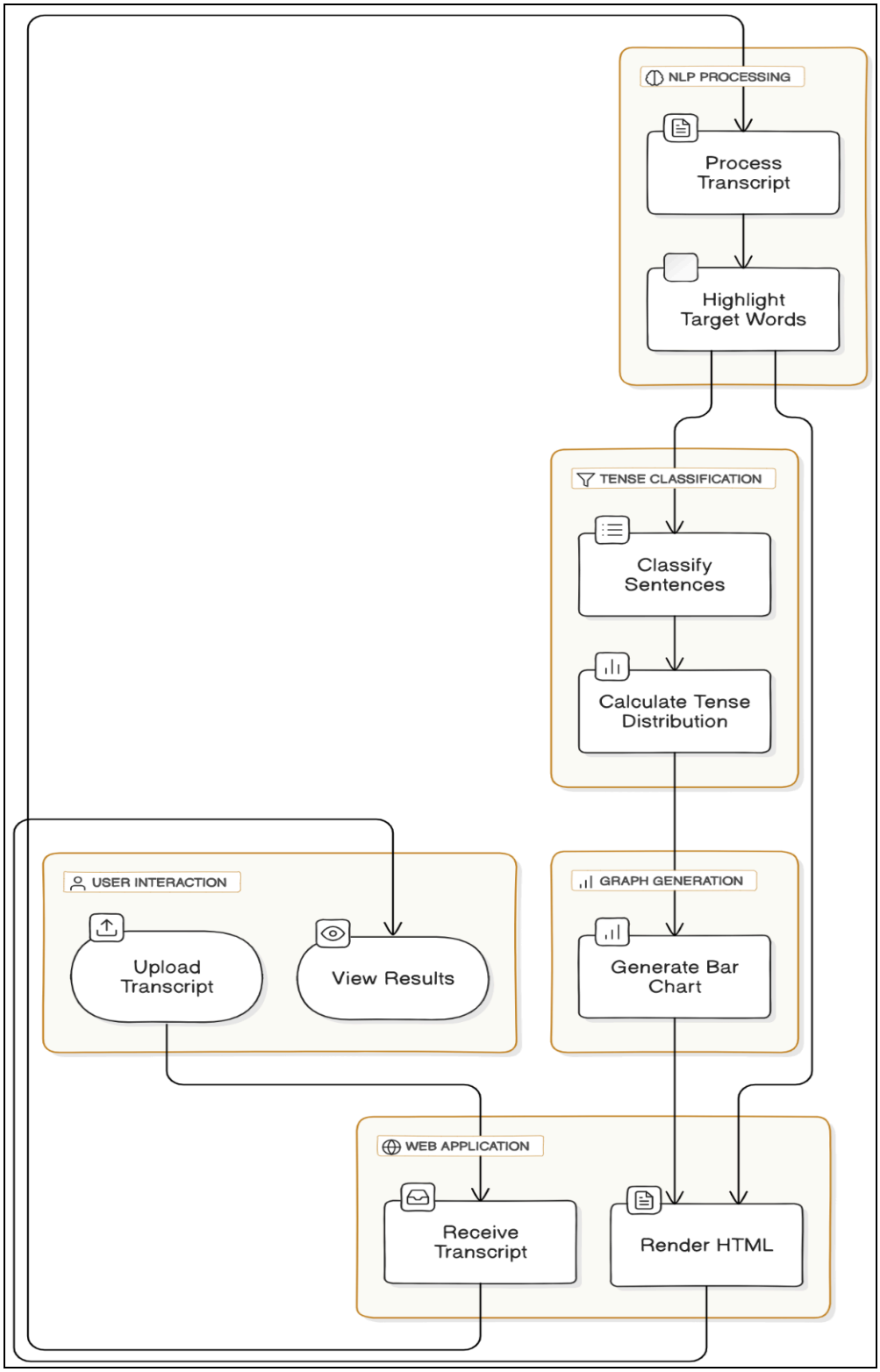


Fig. 4.3.b.3. Flow Chart of Tense distribution

iv. Risk Assessment

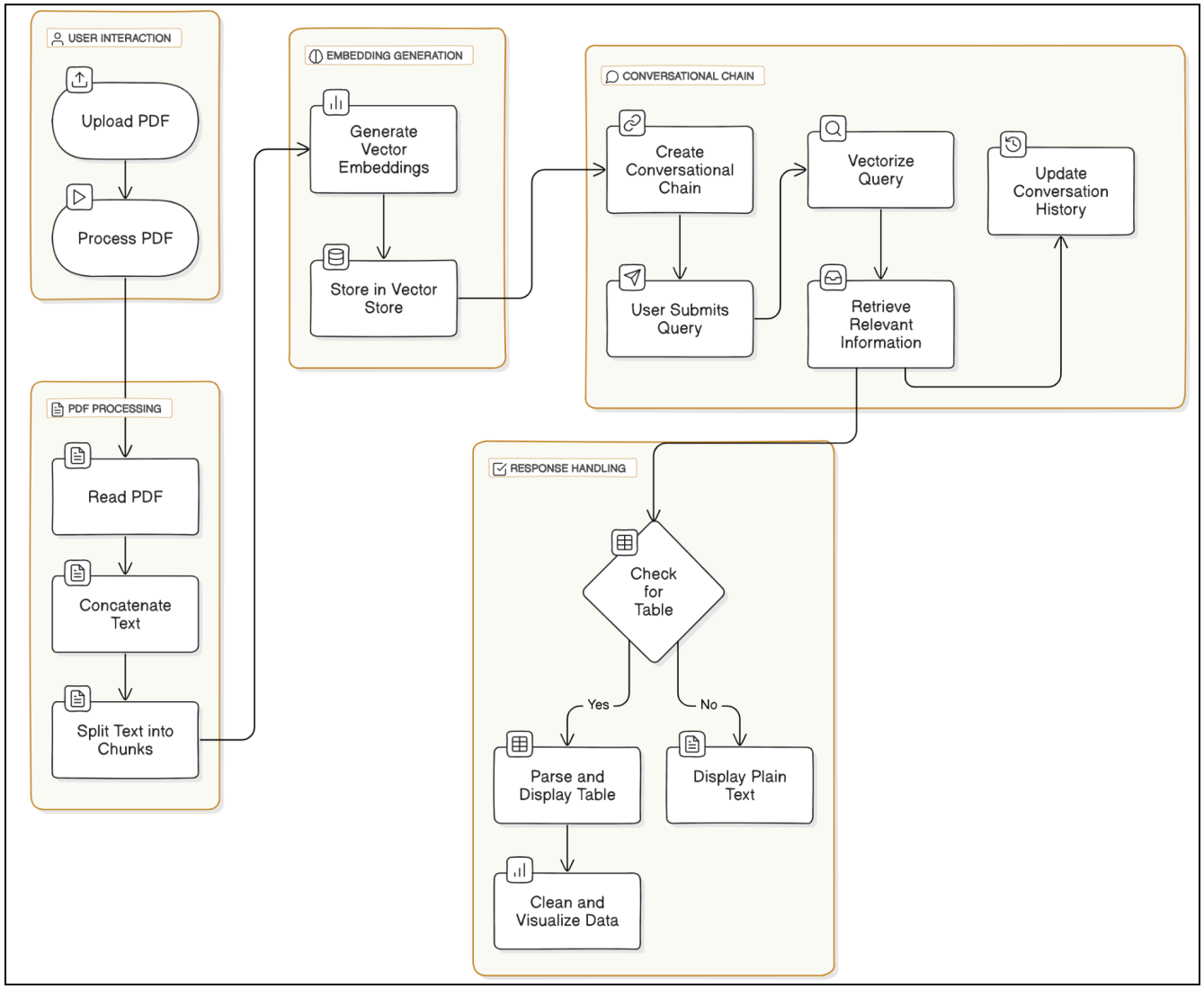


Fig. 4.3.b.4. Flow Chart of Risk Assessment

c. State Transition Diagram

i. Transcription

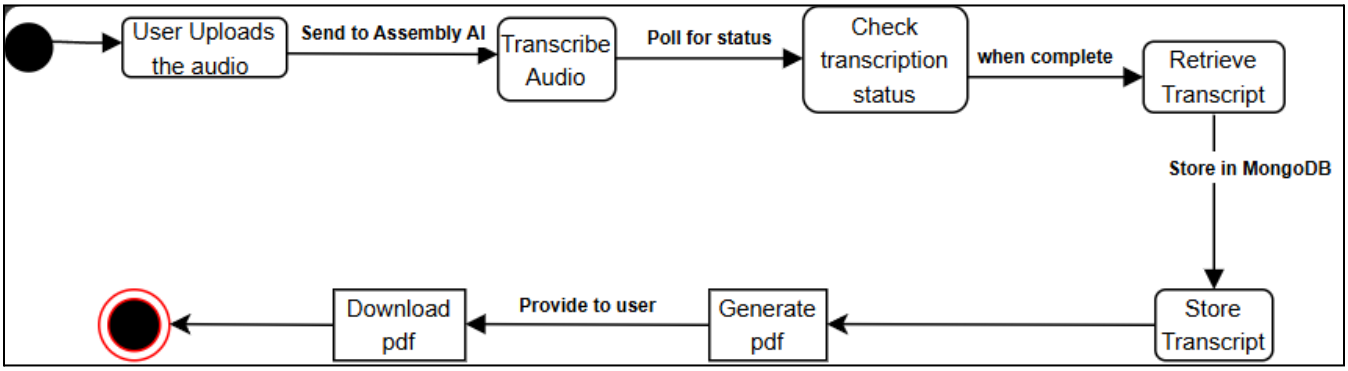


Fig. 4.3.c.1 Transcript Generation State Transition Diagram

This diagram shows the state transitions that occur within the transcription module.

ii. Summarization

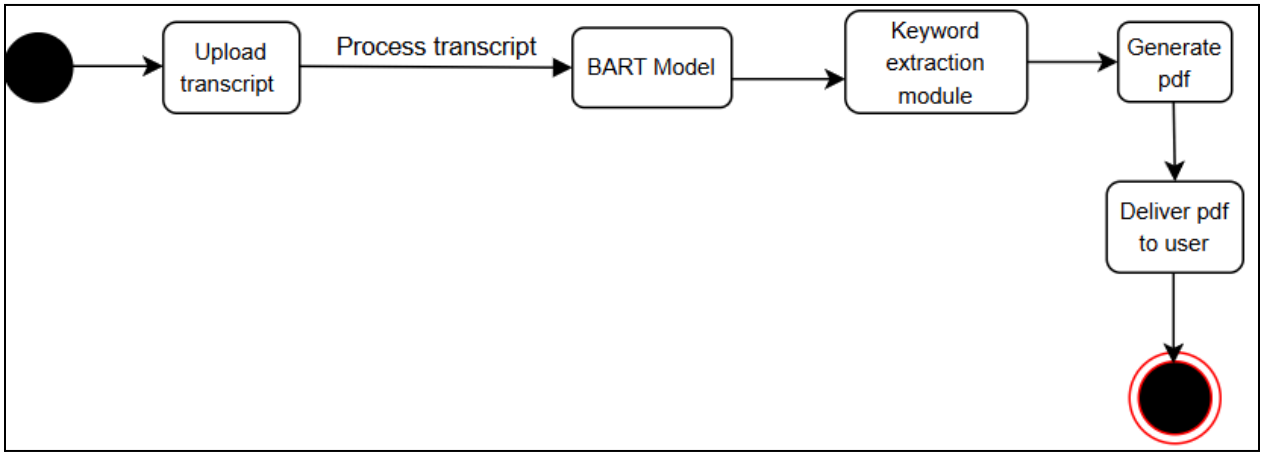


Fig. 4.3.c.2 Transcript Summarization State Transition Diagram

This diagram shows the state transitions that occur within the summarization module.

iii. Timeline Analysis

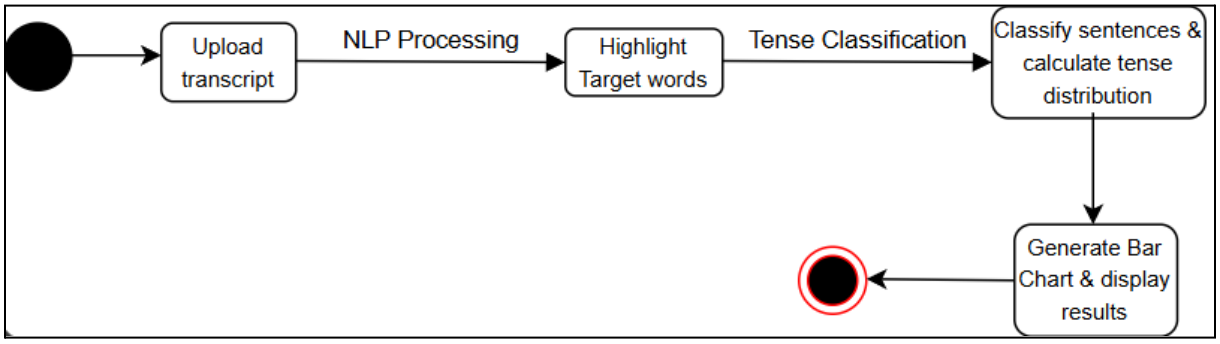


Fig. 4.3.c.3 Timeline Analysis State Transition Diagram

This diagram shows the state transitions that occur within the timeline analysis module.

iv. Risk Assessment

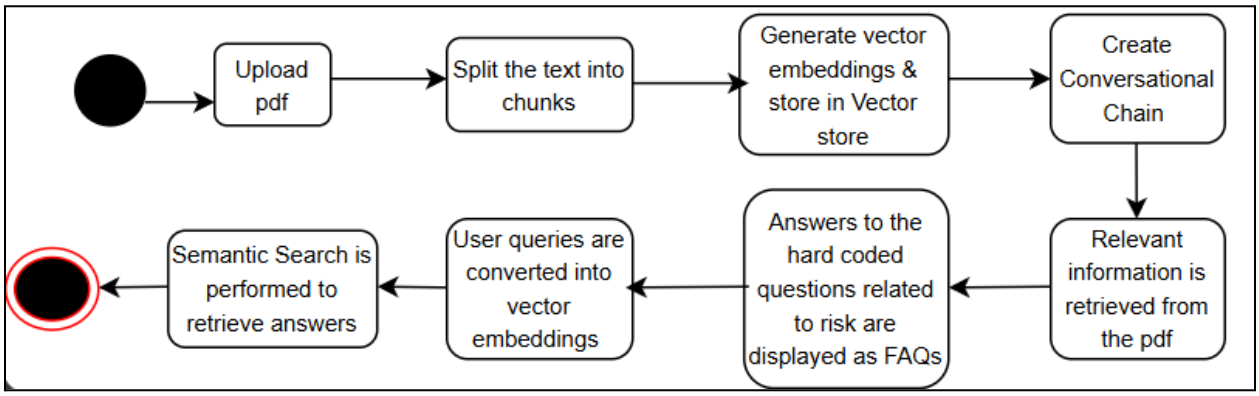


Fig. 4.3.c.4 Risk Assessment State Transition Diagram

This diagram shows the state transitions that occur within the risk assessment module.

d. ER Diagram

i. Transcription

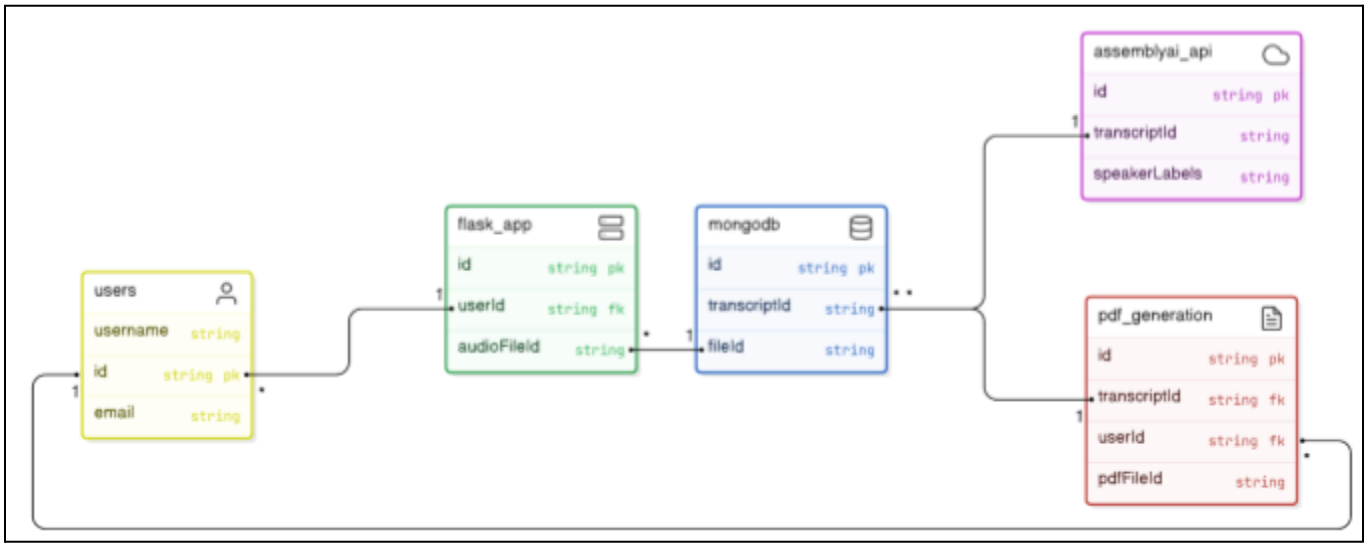


Fig. 4.3.d.1. ER diagram of Transcription

This diagram shows how each entity is connected to each other in the Transcription module.

ii. Summarization

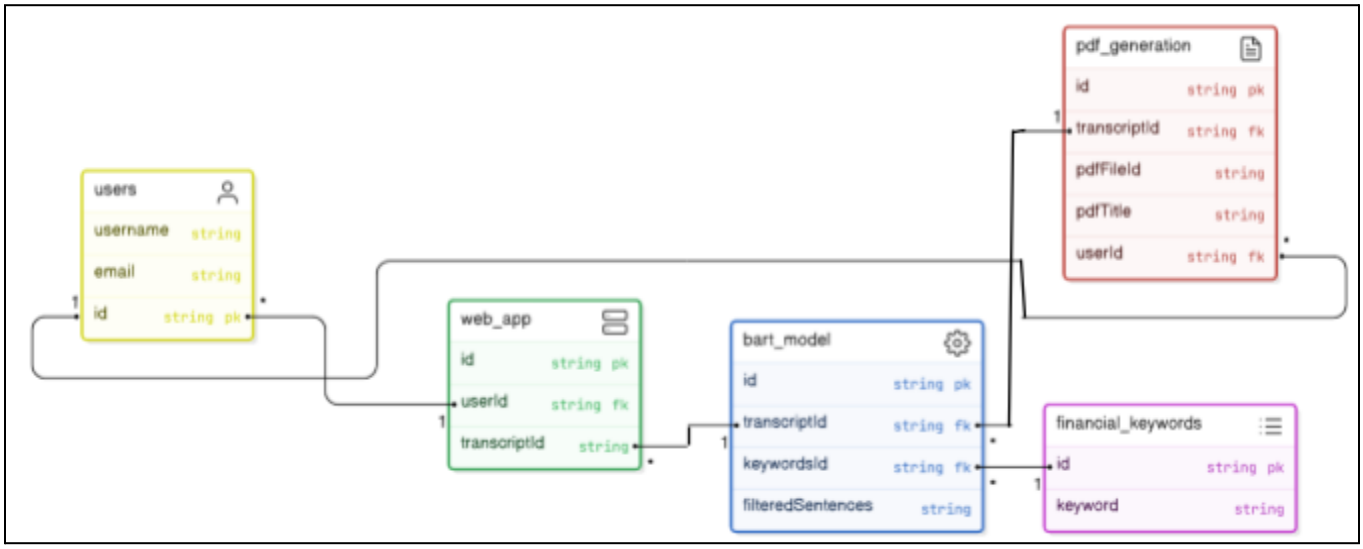


Fig. 4.3.d.2. ER diagram of Summarization

This diagram shows how each entity is connected to each other in the Summarization module.

iii. Timeline Analysis

Fig. 4.3.d.3. ER diagram of Timeline Analysis

This diagram shows how each entity is connected to each other in the Timeline Analysis module.

iv. Risk Assessment

Fig. 4.3.d.4. ER diagram of Risk Assessment

This diagram shows how each entity is connected to each other in the Risk Assessment module.

e. System Architecture

a. Earnings Call Analysis Architecture - Transcription and Summarization

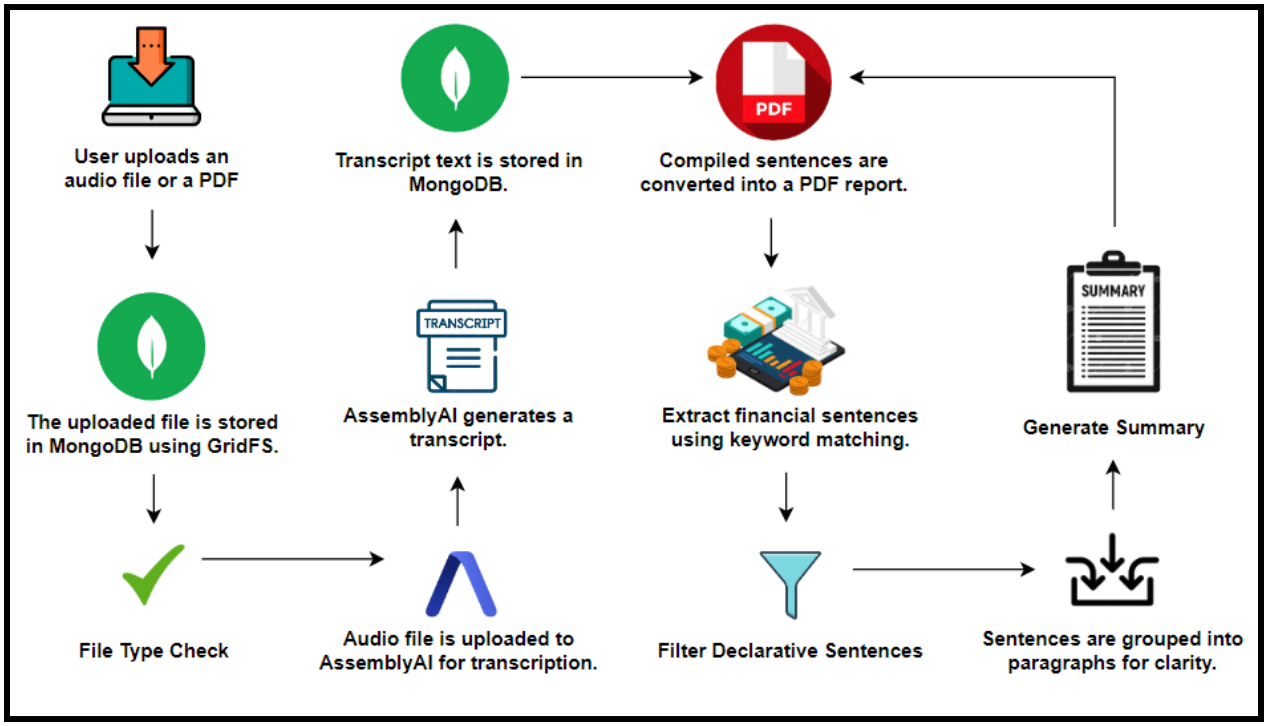


Fig. 4.3.e.1. System Architecture of Earnings call - Transcription and Summarization

1. **Transcript Generation**

   In this study, a system is implemented that facilitates the generation and storage of earnings call transcripts utilizing AssemblyAI's API services. The process begins when an audio file containing the earnings call is uploaded by the user through a dedicated Flask-based web application. This system is designed to handle both audio and PDF files, providing a robust framework for transcription and document analysis.

   a. **Audio File Upload and Storage**

      Upon receiving an audio file via the /upload_files endpoint, the system initiates the following sequence of operations:

      i. File Handling and Storage

      The audio file is first captured from the request and stored in a MongoDB database using GridFS, which is a specification for storing and retrieving large

files in MongoDB. This ensures that the file is stored efficiently, allowing for subsequent access and processing.

ii. File Upload to Assembly AI

The stored audio file is then read in chunks and uploaded to AssemblyAI's transcription service via their API. This step involves streaming the audio data directly to AssemblyAI's servers using the provided API key, which ensures secure and authenticated access.

iii. Transcription Request

Upon successful upload, the system makes a transcription request to AssemblyAI by providing the URL of the uploaded audio file. The request is configured to enable speaker labeling, which distinguishes between different speakers in the transcript.

b. Transcription Polling and Result Retrieval

The transcription process is asynchronous; hence, the system implements a polling mechanism to check the status of the transcription at regular intervals. The following steps are performed:

i. Polling Mechanism

The system repeatedly sends GET requests to AssemblyAI's polling endpoint, using the unique transcription ID obtained from the initial transcription request. This continues until the transcription is marked as complete.

ii. Error Handling

If the transcription process encounters an error, the system captures and returns the error message to the user, allowing for debugging or resubmission of the audio file.

iii. Transcript Storage

Once the transcription is complete, the system retrieves the transcript text, including speaker labels and the corresponding dialogue. The transcript is then stored in the MongoDB database using GridFS, ensuring it is easily accessible for future use.

c. PDF Conversion and Response

In addition to generating and storing the transcript, the system provides an option to convert the transcript into a PDF document. This is accomplished through the following steps:

i. PDF Generation

The system uses the ‘reportlab’ library to format the transcript text into a structured PDF document. Each speaker’s dialogue is encapsulated in a paragraph with proper styling.

ii. Temporary File Handling

The generated PDF is temporarily stored in the system's memory, allowing it to be sent back to the user as a downloadable file.

iii. File Response

Finally, the system serves the generated PDF file to the user via the ‘/getTranscript’ endpoint, facilitating easy access and download.

2. Transcript Summarization

In this study, a system was developed to generate a financial summary from an earnings call transcript. The transcript, which is assumed to be in plain text format, undergoes a series of processing steps to identify and summarize key financial information.

a. **Input Processing**
   The system begins by loading a pre-trained language model and tokenizer, specifically the BART model (facebook/bart-large-cnn), which is optimized for text summarization tasks. The input text is then parsed to identify sentences that are declarative in nature, filtering out interrogative or non-declarative statements to focus solely on factual information.

b. **Keywords-based Sentence Extraction**
   A predefined list of financial keywords is employed to isolate sentences relevant to financial performance. This list includes over 60 terms such as "earnings," "revenue," "profit," "liabilities," and "cash flow." Using regular expressions, the system scans the input text to extract sentences that contain any of these keywords. This method ensures that only sentences with a direct connection to financial matters are included in the summary.
   Keywords: 'earnings', 'revenue', 'profit', 'loss', 'cash flow', 'ebitda', 'financial performance', 'pbt', 'pat', "net income', 'operating income', 'gross profit', 'expenditure', 'dividend', 'assets', 'liabilities', 'equity', 'interest', 'revenue growth', 'cost of goods sold', 'EBIT', 'EBIT margin', 'depreciation', 'amortization', 'working capital', 'current ratio', 'quick ratio', 'return on equity', 'return on assets', 'profit margin', 'operating margin', 'gross margin', 'cash conversion cycle', 'inventory turnover', 'accounts receivable turnover', 'accounts payable turnover', 'debt to equity ratio', 'interest coverage ratio', 'operating cash flow', 'free cash flow', 'capital expenditure', 'return on investment', 'net profit margin','liquidity ratio', 'solvency ratio', 'inventory days', 'accounts receivable days', 'accounts payable days', 'return on capital employed', 'earnings before tax', 'earnings after tax', 'net profit', 'cost of revenue', 'interest expense', 'net interest income', 'net interest margin', 'shareholder equity', 'capital adequacy ratio'

c. **Summarization and PDF Generation**
   The extracted sentences are then formatted and aggregated into paragraphs, with a new paragraph being created after every 15 sentences. The content is structured into a PDF document, where each sentence is justified for better readability. The PDF document is titled "Transcript Summary," and the company name is prominently displayed. This process not only captures key financial statements but also presents them in a professionally formatted document suitable for distribution.

b. Earnings Call Analysis Architecture - Timeline Analysis

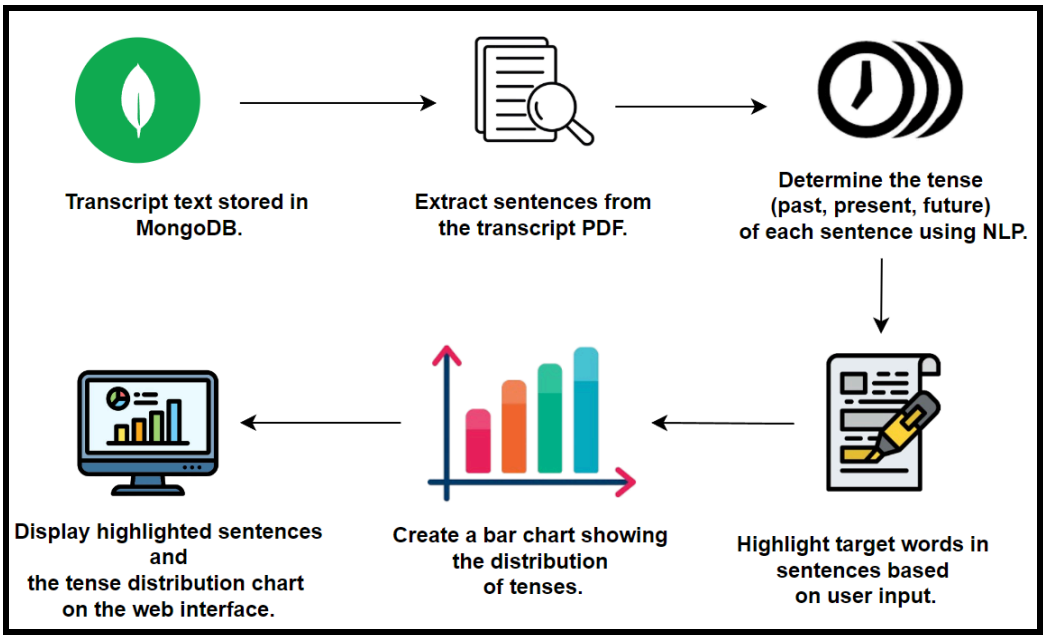


Fig. 4.3.e.2. System Architecture of Earnings Call Analysis Architecture - Timeline Analysis

This feature of the project looks into the time distribution of statements in an earnings call transcript. The input for this feature will be the transcripts generated from an earnings call, which is then processed for the identification and categorization of sentences based on their tense into three categories—past, present, or future. The system does the following:

a. **Tense Detection and Sentence Highlighting**
   This transcript is fed to an NLP model to determine each sentence's tense. The determination of tense comes from a combination of verbs and/or auxiliary words in the sentence.
   i. Tense Classification
   The sentences in the transcript are distinguished according to whether they deal with the past, present, or future. This is achieved by an analysis of the verbs in the sentences.
   ii. Semantic Highlighting
   It highlights sentences containing a target word as specified by the user. In addition, it emphasizes instances of this word in these sentences to give a clearer view of the key terms in different temporal contexts.
b. **Tense Distribution Visualization**
   The distribution of these tenses will then be visualized in the system across the transcript.
   i. Percentage Calculation
   It calculates the percentage of sentences in every category of tense: past, present, and future. In this way, a user can get the emphasis level with respect to different temporal aspects within the earnings call.
   ii. Graph Generation

These percentages are then calculated and plotted in a bar chart so that it will give, at one glance, an illustration of the distribution of the tenses; this chart will be embedded in the output provided to the user.

c. Result Compilation and Response

It systemizes the compiled highlighted sentences and a tense distribution chart in a response.

i. HTML Template Rendering

The user is then redirected to an HTML template with the highlighted sentences and tense distribution chart. As a result, the user can see and use the results right in the web browser.

c. Risk Assessment Architecture

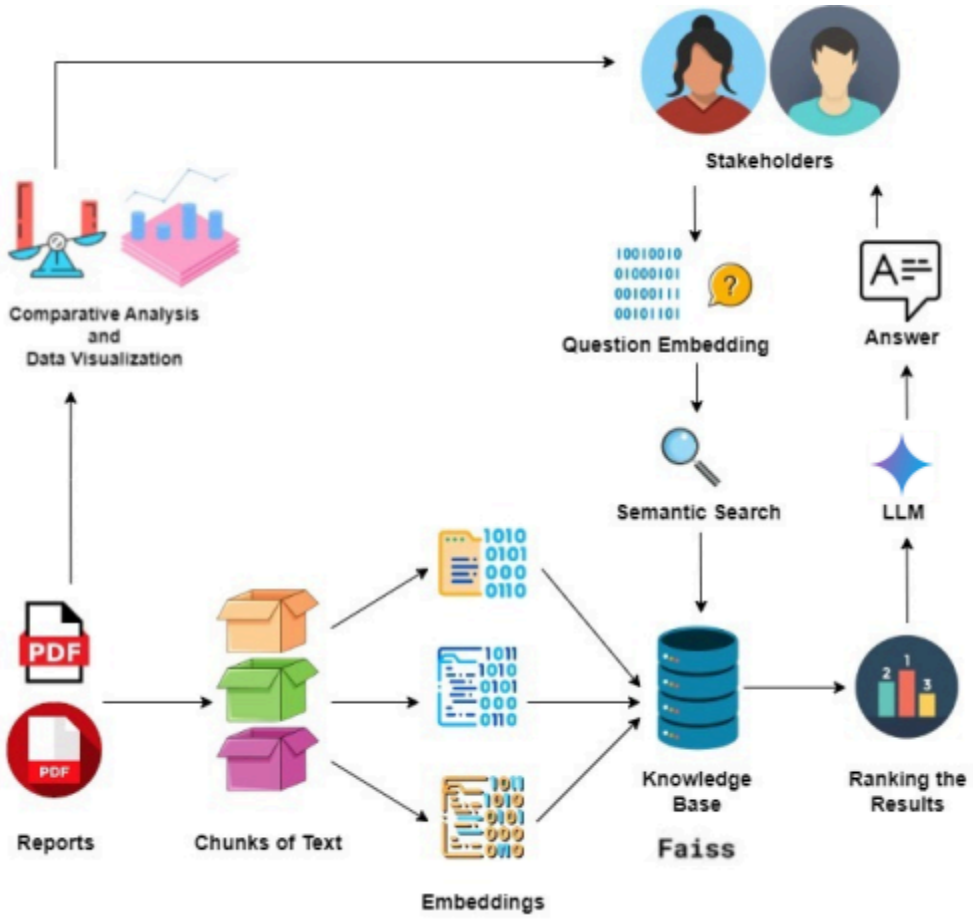


Fig. 4.3.e.3. System Architecture of Risk Assessment Architecture

1. **Uploading Files**
    a. The document is given as input using steamlit's file uploader component.
    b. The user clicks on the 'Process PDF' button.
2. **Processing the Files**

a. The process_pdf() function is called. This function reads the text content from each page of the PDF file using the ‘PdfReader’ from the PyPDF2 library.
b. The text content from each page is concatenated to form a single string representing the entire document.
c. The get_text_chunks() function is called. This function takes the text string as input and splits it into smaller chunks. It uses ‘RecursiveCharacterTextSplitter’ from the LangChain Library to split the text into chunks of size 5000 with an overlapping of 1000.
d. The get_vector_store() function is called. In the context of Natural Language Processing, the Vector store is a data structure which stores the vector representation of textual data. This function takes the text chunk as input. It generates vector embeddings for each text chunk using the Google Generative AI embeddings..These embeddings are stored in a vector store created using the FAISS Library.
e. The get_conversational_chain() function is called. This function creates a conversational chain using the LangChain library. It takes the vector store and a prompt template as input.
f. First, it initializes the gemini-1.5-flash model which is our large language model for generating responses.
g. It creates a memory component 'ConversationBufferMemory' to store the conversation history.
h. The conversational chain is configured to use the provided vector store as a retriever for answering user questions.
i. To construct the conversational chain, it uses the ConversationalRetrievalChain.from_llm() method.
j. The resulting conversation_chain is our configured conversational model capable of retrieving relevant information from the vector store and generating responses to user queries based on the provided prompt template.

3. Handle User Queries

a. Now as the PDFs are processed, the user enters a question and clicks on get response.
b. The user_input function is called. It takes the user’s question as input. This function interacts with the conversational chain stored in the streamlit session state to retrieve a response.
c. The vector representation of the query is created and is compared with the vector representations present in the vector store.
d. The most similar vectors are then retrieved based on the similarity.
e. The conversation history is updated and displayed to the user.

4. Displaying the Response

a. First, the code checks if there is any conversation history stored in streamlit session state. If it is there, it iterates through each message in the history.
b. For each message, it checks if the message index (‘i’) is even or odd. If it is even, it is the user's message and if it is odd, it is the bot's message.
c. If it is the response, it checks if the response contains table formatting by looking for ‘|’ and ‘---’ characters.
d. If yes, then it parses the response into a dataframe, eliminates dirty values and displays it as a table.
e. Then, it extracts the data from the table into a data.csv file.
f. This data is string data. It contains words like million, billion, M, B, %, $, etc. We convert those characters into empty string and then the entire value into float and plot the graph.
g. But, if there is no table in the response, it is displayed as a plain text.

5. **Generating Risk Related FAQs**
   a. We have predefined categories and questions.
   b. The response is retrieved the same way as user queries are answers.

5. Proposed Results and Discussions

- **Earnings Call Analysis Module**

Fig.5 Landing page of Earnings Call module

This is the home page of Earnings Call Analyzer module

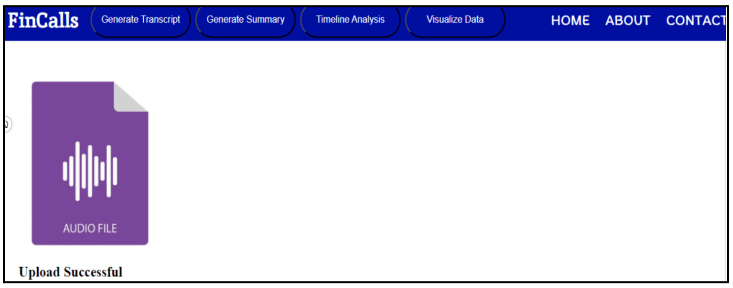


Fig. 6 User successfully uploaded the earnings call

The earnings call was successfully uploaded by the user.

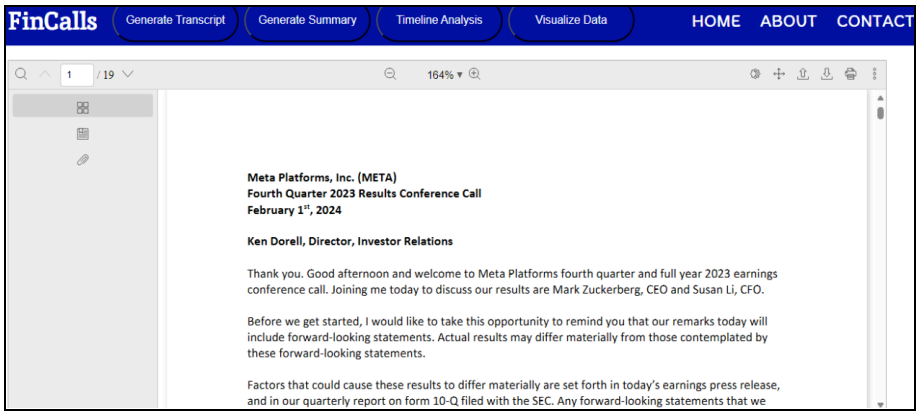


Fig. 7 Transcript generation result

The transcript of the Earnings call was generated (19 pages)

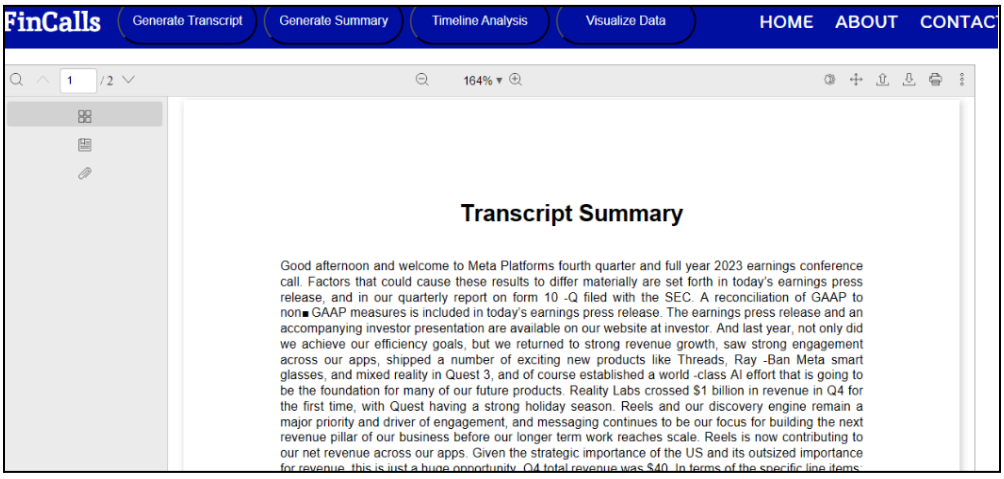


Fig 8. Transcript summary generated

Here, the summary of transcript is generated (2 pages)

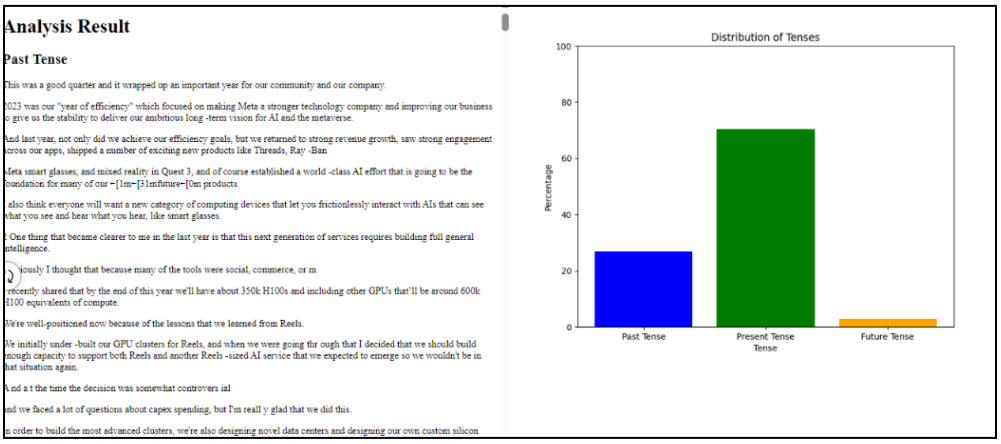


Fig 9. Timeline Analysis generated

The timeline analysis of the Earnings call generated, where the user can study how much of the whole call was discussed about the past events, the present condition and the future plannings.

- **Risk Assessment**
  The input taken here is a sample document which contains some information about the company.

XYZ Corporation Financial Overview

In the fiscal year ending December 31, 2023, XYZ Corporation reported a total revenue of $1.2 billion, reflecting a modest increase of 5% compared to the previous year. However, the company's net profit experienced a significant decline, dropping by 15% to $150 million. This downturn is attributed to rising operational costs and increased competition in the market.

XYZ Corporation has implemented several strategic initiatives to address these challenges. The company has invested heavily in technology upgrades, allocating $100 million towards enhancing its digital infrastructure and improving operational efficiencies. This strategic pivot aims to streamline processes and reduce costs in the long run.

Despite these efforts, the company acknowledges the inherent risks associated with its expansion strategy. The volatility in raw material prices poses a threat to profit margins, as indicated by a 10% increase in material costs over the past year. Additionally, the ongoing geopolitical tensions in key markets have raised concerns regarding supply chain stability, potentially impacting product availability and pricing.

Looking forward, XYZ Corporation remains committed to diversifying its product offerings and exploring new market opportunities. The management team is optimistic about achieving a revenue target of $1.5 billion by the end of 2024. However, they also caution that achieving this goal will require navigating significant market uncertainties, including regulatory changes and economic fluctuations.

In summary, while XYZ Corporation has laid out a comprehensive strategy to enhance profitability and growth, the company remains vigilant of the risks that could affect its financial health and operational success.

Fig. 10 Input Document of Risk Assessment module

The input here is a sample document that provides details about the company.

Statements Depicting Risk:

- "The company's net profit experienced a significant decline, dropping by 15% to $150 million."
- "This downturn is attributed to rising operational costs and increased competition in the market."
- "The volatility in raw material prices poses a threat to profit margins, as indicated by a 10% increase in material costs over the past year."
- "Additionally, the ongoing geopolitical tensions in key markets have raised concerns regarding supply chain stability, potentially impacting product availability and pricing."
- "Despite these efforts, the company acknowledges the inherent risks associated with its expansion strategy."
- "However, they also caution that achieving this goal will require navigating significant market uncertainties, including regulatory changes and economic fluctuations."

Fig. 11 Statements Depicting Risk

Here we extract the statements that depict risk for the stakeholders.

Negative Impact Statements:

- "The company's net profit experienced a significant decline, dropping by 15% to $150 million."
- "Rising operational costs"
- "Increased competition in the market"
- "10% increase in material costs over the past year"
- "Concerns regarding supply chain stability, potentially impacting product availability and pricing"
- "Significant market uncertainties, including regulatory changes and economic fluctuations"

Fig. 12 Negative Impact Statements

The sentences that show negative impact for the stakeholders.

- **Negative:** Net profit decreased by 15% to $150 million.
- **Negative:** Material costs increased by 10% over the past year.
- **Positive:** Revenue increased by 5% to $1.2 billion.
- **Positive:** Investment in technology upgrades: $100 million.
- **Target:** Revenue target of $1.5 billion by the end of 2024.

Fig. 13 Quantifiable data classified into positive and negative trends

We classify the quantifiable data into positive and negative trends.

Assessment Summary:

XYZ Corporation faces several significant risks that could impact its financial health and operational success.

- **Profitability Decline:** The company experienced a substantial decline in net profit, attributed to rising operational costs and increased competition. This trend could continue if not addressed effectively.
- **Raw Material Price Volatility:** Fluctuations in raw material prices pose a threat to profit margins, as evidenced by the 10% increase in material costs. This could further impact profitability if not mitigated.
- **Supply Chain Disruptions:** Geopolitical tensions and potential supply chain disruptions could negatively impact product availability and pricing, affecting both revenue and customer satisfaction.
- **Market Uncertainties:** Regulatory changes and economic fluctuations add to the existing challenges, requiring careful navigation and strategic adjustments to achieve the targeted revenue growth.

Fig. 14 Risk Assessment of all the extracted data

We get the risk assessment of all the data that is extracted.

Risk Mitigation Suggestions:

- **Cost Optimization:** Implement cost reduction strategies across all operations to address the rising operational costs. This could include streamlining processes, negotiating better deals with suppliers, and exploring alternative sourcing options.
- **Competitive Differentiation:** Develop a strong competitive strategy to address the increasing market competition. This could involve product innovation, targeted marketing campaigns, and enhancing customer service.
- **Raw Material Hedging:** Explore hedging strategies to mitigate the impact of raw material price volatility. This could involve using forward contracts or other financial instruments to lock in prices.
- **Supply Chain Diversification:** Diversify supply chains to reduce reliance on specific regions and minimize the impact of geopolitical tensions. This could involve sourcing materials from multiple locations or establishing alternative manufacturing facilities.
- **Strategic Market Analysis:** Continuously monitor regulatory changes and economic fluctuations to proactively adapt the business strategy. This could involve conducting regular market research, engaging with industry experts, and developing contingency plans.

By actively addressing these risks and implementing mitigation strategies, XYZ Corporation can improve its resilience and enhance its chances of achieving its ambitious growth targets.

Fig. 15 Risk Mitigation Suggestions

Suggestions about Risk Mitigation from the document given as input is provided.

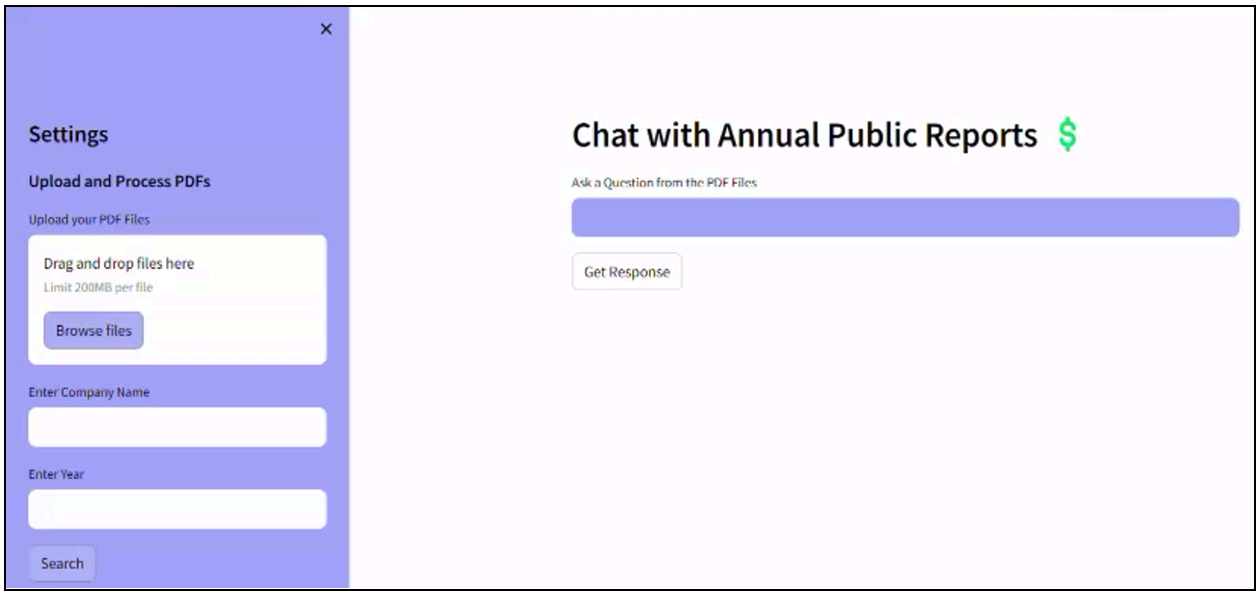


Fig. 16 ChatBot Home Page

This is the home page of the Chatbot.

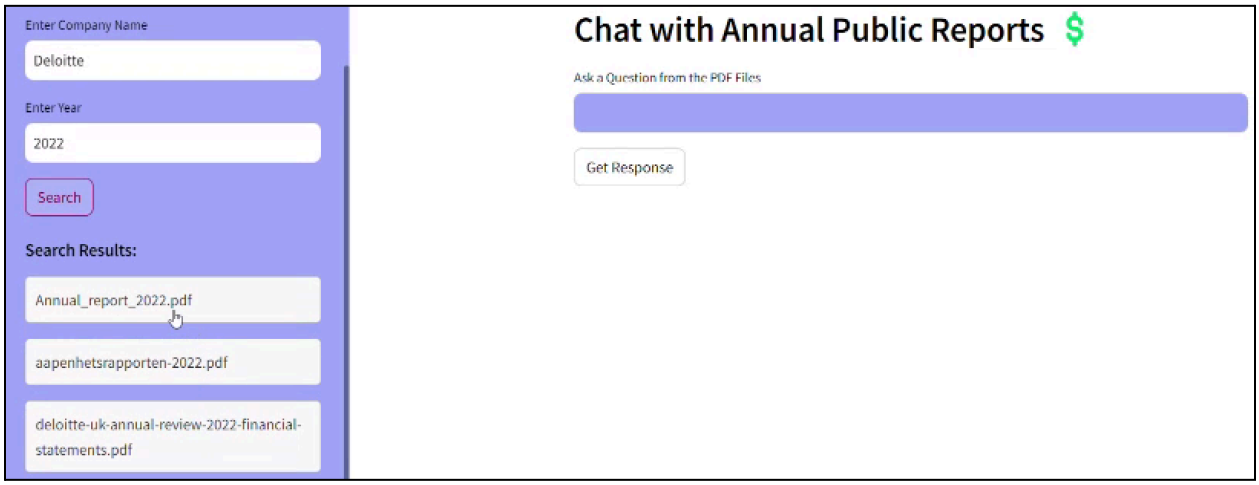


Fig. 17 Search company name and year

We get the results after entering the name of any company and particular year (Deloitte and 2022 in this case), that is all the documents available over the net related to Deloitte and 2022.

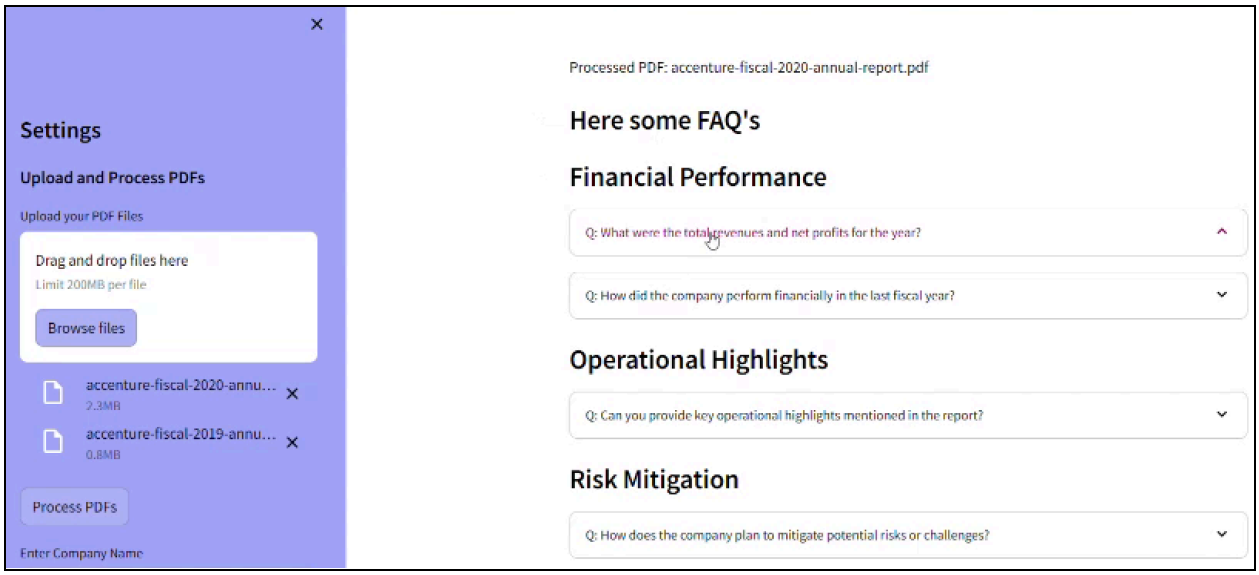


Fig. 18 FAQs generated

FAQs generated category wise with answers taken from the 2 uploaded PDFs

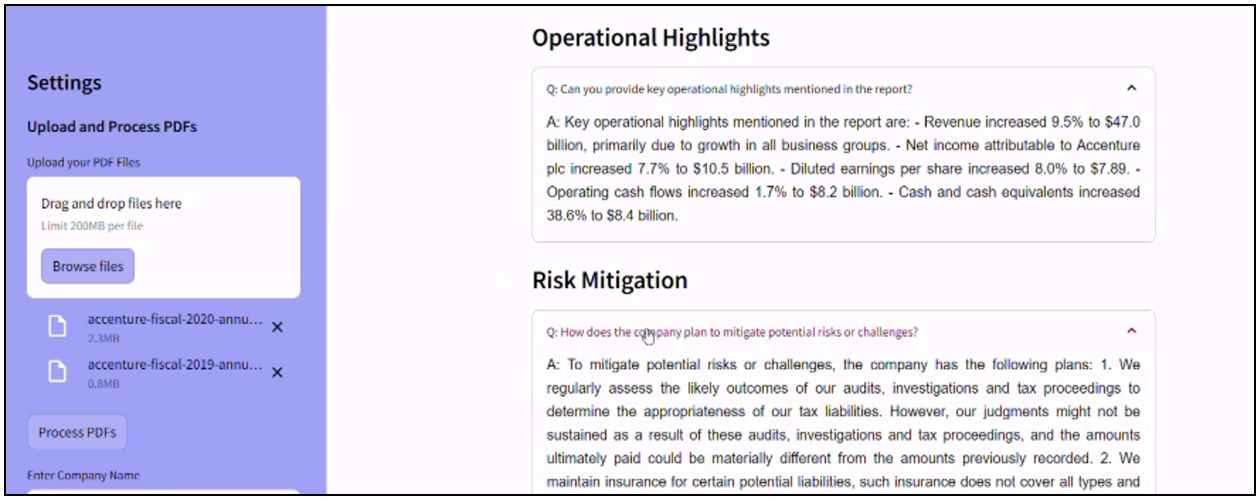


Fig. 19 Answers of the FAQs

Few answers retrieved from the two input documents in FAQ section

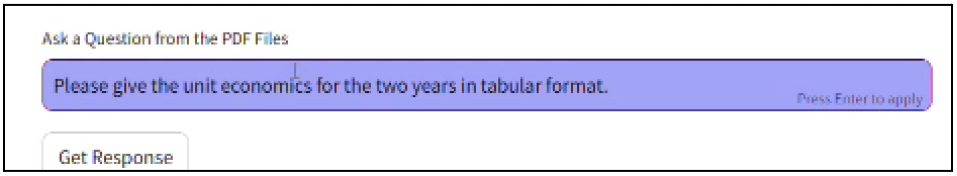


Fig. 20 Question entered by the user

The user can enter any query in the query box.

	Metrics	Fiscal 2020	Fiscal 2019
0	Revenues	$44,327 million	$43,215 million
1	Cost of services	$36,181 million	$35,303 million
2	Gross margin	31.5%	30.8%
3	Sales and marketing costs	$7,350 million	$7,237 million
4	General and administrative costs	$7,524 million	$7,325 million
5	Operating income	$5,412 million	$4,655 million
6	Operating margin	14.7%	11.0%
7	Diluted earnings per share	$7.89	$7.36

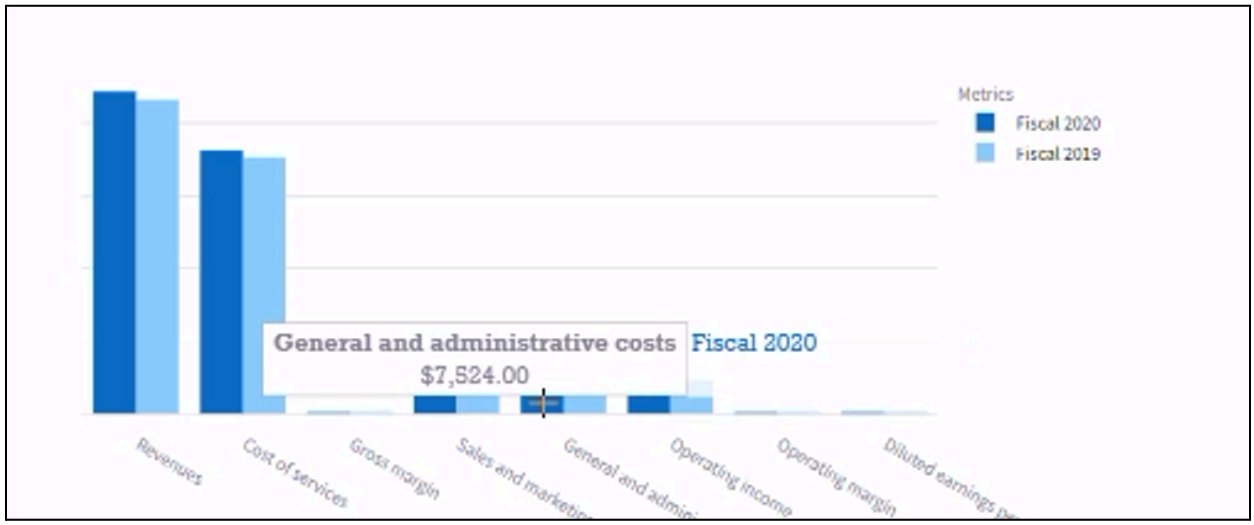


Fig.21 Answer to the given question

The chatbot will get the asked data from the pdf and represent the data in tabular form with visual representation (graphs), if visualization is possible.

6. Plan of Action for the next Semester

6.1 Work done till date

As of now, the Fincalls - Risk Analyzer project has successfully implemented several critical components designed to streamline the analysis of corporate earnings calls and associated financial documents. The key achievements include:

1. **Earnings Call Analysis**:
    a. **Transcript Generation**: Users can upload audio files of earnings calls, which are processed through AssemblyAI's API to generate accurate transcripts. The transcripts are stored in MongoDB for easy retrieval.
    b. **Summarization**: The system leverages a pre-trained BART model to summarize the transcripts, focusing on extracting essential financial metrics and insights relevant to investors.
    c. **Timeline Analysis**: The analysis categorizes statements within the transcripts by tense (past, present, future), allowing users to understand the temporal context of financial discussions.
2. **Chatbot Functionality**:
    a. Users can upload multiple documents and engage in a chat interface that allows for dynamic interactions with the data.
    b. The system performs comparative analysis across different documents and enables users to search for specific company-related articles from the web, which can be downloaded for further review.
3. **Risk-Related FAQs**:
    a. The system generates FAQs based on the uploaded PDF documents, addressing common risk-related queries and providing users with quick access to relevant information.

With these foundational elements in place, the system is poised to deliver valuable insights and risk assessments to investors, enhancing their ability to make informed decisions.

6.2 Plan of action for project II

To further enhance the Fincalls - Risk Analyzer, the following plan of action outlines the next steps needed to complete the project:

1. Tone Analysis:
    a. Implement a tone analysis feature that evaluates the sentiment and emotional tone of the earnings call transcripts. This analysis will help users gauge management's confidence and perspective during the call, which can significantly impact investor perception.
2. Integration of News Articles as Input Sources:
    a. Develop functionality to accept news articles related to the company as an additional input source for risk assessment. This will involve extracting relevant content from news articles, which can then be analyzed for risk factors that may affect the company's performance.
3. Comprehensive Risk Analysis Report:
    a. Create a full-fledged risk analysis report that synthesizes findings from all four input sources:
        i. Earnings Call Audio Transcripts: Summary and tone analysis.
        ii. Financial Reports: Detailed analysis of financial performance metrics.
        iii. News Articles: Insights from recent news articles that may influence risk factors.
        iv. User-Uploaded Documents: Integration of user-provided PDFs for holistic risk evaluation.
    b. This report will compile the findings into a structured format, highlighting key risk areas, potential mitigation strategies, and actionable recommendations for investors.

By executing this plan, the Fincalls - Risk Analyzer will evolve into a comprehensive tool that not only analyzes earnings calls but also considers broader market sentiments and news dynamics, providing a well-rounded risk assessment for users.

7. Conclusion

The Fincalls - Risk Analyzer project represents a significant advancement in the landscape of financial analysis tools, specifically designed to empower investors with a comprehensive understanding of corporate earnings calls and their associated risks. Through the seamless integration of cutting-edge technologies such as AssemblyAI for transcription, BART for summarization, and LangChain for conversational AI, the system effectively transforms complex audio and textual data into actionable insights.

By successfully implementing core functionalities such as transcript generation, summarization, timeline analysis, and an interactive chatbot interface, the project has laid a solid foundation for users to navigate the intricacies of financial communications. The capability to extract critical financial metrics, analyze temporal context, and engage in dynamic discussions enhances the user experience and fosters informed decision-making.

Looking forward, the planned enhancements, including tone analysis and the integration of news articles, will further enrich the platform's analytical capabilities. This comprehensive approach ensures that users are not only equipped with insights derived from earnings calls but also provided with a broader context from external news sources, culminating in a well-rounded risk assessment report.

In conclusion, the Fincalls - Risk Analyzer stands poised to redefine how investors interact with corporate earnings data, bridging the gap between raw financial information and strategic investment decisions. As the project continues to evolve, it promises to deliver greater value, enabling users to navigate the complexities of the financial landscape with confidence and clarity.

8. References

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1. Appendix

1.1. List Of Figures

1.2. List Of Tables