AI-QADS: AI-Powered Query Analysis And Document Systems

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Abstract- *This project aims to develop an AI-powered financial document analysis system that leverages the Groq LLM and advanced natural language processing techniques to extract, summarize, and analyze critical financial data from complex documents such as balance sheets, income statements, and cash flow statements. The approach involves chunking financial documents, embedding text using Sentence Transformer, and storing structured data in a knowledge base for efficient retrieval. A Retrieval-Augmented Generation (RAG)-based chatbot enables interactive querying, allowing users to extract relevant insights seamlessly. Furthermore, the system explores the potential of large language models in financial forecasting by employing a Chain-of-Thought prompting methodology to guide the model through an analysis process that mirrors expert reasoning. Despite the advancements in natural language processing, challenges persist in AI's ability to independently analyze numerical data and make financial judgments requiring contextual industry knowledge. This project aims to assess the capabilities and limitations of AI in financial statement analysis, bridging the gap between automated processing and human expertise to support more informed, data-driven business decisions.*

Keywords- AI-based Query Analysis and Document System,llama 3.3 70b versatile.

I. INTRODUCTION

Financial document analysis is vital for informed business decisions. The Groq LLM enhances efficiency by summarizing key financial data using chunking, embedding (Sentence Transformer 'all-MiniLM-L6-v2'), and knowledge base storage for quick retrieval.

Our system integrates chatbot functionality with Retrieval-Augmented Generation (RAG), enabling users to interact and extract insights efficiently. It processes diverse financial documents, identifying trends and anomalies with scalability for large volumes.

While LLMs aid analysis, they lack reasoning, contextual judgment, and numerical processing capabilities. We investigate LLMs in financial analysis using Chain-of-Thought prompting, benchmarking performance against human expertise.

This solution leverages Groq LLM to provide seamless, data-driven insights, enhancing financial analysis for businesses in a complex landscape.

A. Existing Research and Industry Gaps

This project enhances financial document analysis by automating manual processes, reducing paper-based documentation, and aligning with sustainability initiatives. By digitizing financial workflows, it minimizes reliance on physical records, leading to reduced operational costs and environmental benefits. Economically, automation lowers human errors, improving data accuracy and decision-making while optimizing resource allocation for better financial performance.

The integration of large language models (LLMs) into financial analysis has gained significant attention due to their ability to process complex data efficiently. Researchers are investigating how LLMs can complement traditional financial analysis by identifying trends, generating insights, and improving predictive accuracy. Despite their potential, challenges such as data security, model biases, and regulatory compliance must be addressed for seamless industry adoption.

II. LITERATUREREVIEW

Traditional financial analysis relies on human expertise, with analyst forecasts achieving 52.71% accuracy, slightly better than naive models (49.11%). Recent research shows that LLMs with structured reasoning (CoT prompting) reach 60.35% accuracy, improving financial insights. However, gaps remain in real-time data integration, industry-specific knowledge, and regulatory compliance. This project aims to bridge these gaps by developing an AI-powered financial document analysis system, enhancing accuracy and efficiency in decision-making.

A. Comparative Analysis of Existing and AI-Powered Query Analysis Systems

Query Analysis and Document System	Strengths	Limitations
AI-Based Query Processing	Provides fast and accurate responses to complex queries	Requireslarge datasets for training
Automated Document Classification	Efficiently categorizes documents, reducing manual effort	May misclassify non-standardized documents
Natural Language Understanding (NLU)	Enhances user interaction with intelligent query handling	Struggles with ambiguous or incomplete queries
Real-Time Data Extraction	Extracts key insights instantly, improving decision-making	Can be computationally expensive

Table1:StrenghtandLimitationsofthetraditionalmethods

B. Research Gaps and Need for AI-QADS Enhancer

Lack of Real-Time Threat Detection – Existing financial document security systems struggle to detect and respond to evolving cyber threats in real time.

Inaccurate Query Analysis – Traditional AI models often misinterpret complex financial queries, leading to errors in data extraction and decision-making.

Data Privacy and Compliance Challenges – Many systems fail to provide robust encryption and compliance measures required for financial data security.

Limited Scalability and Adaptability – Current solutions lack flexibility to scale with increasing data loads and changing security threats.

Manual Dependency in Fraud Detection – Many financial systems still require human intervention for fraud detection, increasing the risk of oversight and inefficiencies.

III. METHODOLOGY

The project utilizes Large Language Models (LLMs) to automate financial document analysis, reducing manual effort and improving accuracy. It begins with *data collection and preprocessing, followed by LLM-based analysis using Chain-of-Thought (CoT) prompting for enhanced reasoning. Users can upload documents, query insights, and generate reports via an *interactive interface, backed by a database and API-driven architecture. Rigorous testing and validation ensure reliability, while cloud deployment* enables scalability. This approach optimizes resource allocation, minimizes errors, and enhances decision-making in financial analysis.

A. System Architecture

1. **Data Ingestion and Preprocessing** – The system collects financial documents from multiple sources, processes them using AI-powered algorithms, and structures the data for efficient analysis.
2. **AI-Powered Query and Analysis Module** – This module leverages *large language models (LLMs)to interpret user queries, extract relevant financial insights, and generate accurate responses.
3. **Security and Compliance Layer** – Ensures data encryption, access control, and regulatory compliance to safeguard sensitive financial information.
4. **User Interface and Reporting**– Provides an intuitive dashboard where users can upload documents, query financial data, generate reports, and receive real-time insights with minimal manual effort.

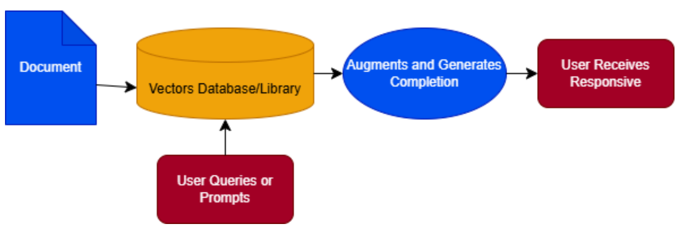


Figure1:SystemArchitecture

B. Workflow Process

1. **Document Upload & Preprocessing**– Users upload financial documents, which are scanned and structured for analysis.
2. **AI-Powered Data Extraction & Query Processing** – The system utilizes LLMs to extract key financial insights and respond to user queries accurately.
3. **Report Generation & Validation** – Processed data is compiled into structured reports, ensuring accuracy and compliance.
4. **Secure Storage & Access Management** – Financial documents and analysis results are securely stored, with controlled access for authorized users.

IV. IMPLEMENTATION

A. Tools and Technologies Used

The system is built using a combination of deep learning, backend services, and mobile integration technologies**.**

Component	Technology Used
Document Upload and Processing	Streamlit (UI), pdf.js
Text Preprocessing	Python (Data Cleaning Techniques)
Embedding and Storage Management	Sentence Transformers, SQL/Vector Databases
Data Chunking	Text Chunking Algorithms
Efficient Data Retrieval	Scalable Database Architecture
Interactive Chatbot Workflow	Retrieval-Augmented Generation (RAG)
Query Processing	GROQ LLM ("llama-3.3-70b-versatile")
Response Generation	AI-Powered NLP Models
User Interaction Enhancement	Conversational AI Integration

Table2:the work function and technology we used

B. Step-by-Step Execution

1. Document Upload & Preprocessing

- Users upload financial documents in various formats (PDF, Excel, scanned images).
- Text normalization is performed to clean and structure the extracted data.

2. AI-Powered Query Analys If a financial query is entered:

- The system interprets the query using Natural Language Processing (NLP).
- Relevant financial data is retrieved from the document database.
- Key metrics are extracted and presented in a structured format.

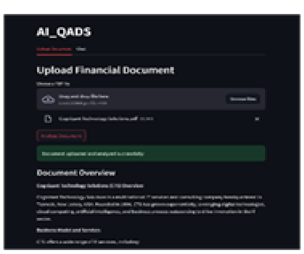
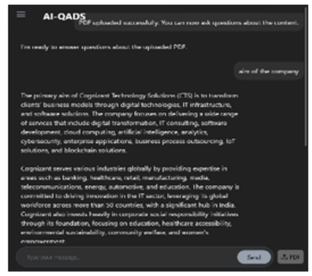


Figure2:UI document Uploaded

3. Automated Data Processing & Report Generation

- Email Extracted financial data is categorized into relevant sections.
- AI-driven analysis identifies key trends and anomalies.
- Reports are generated in a structured format for user review.



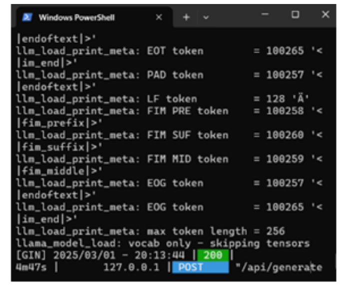
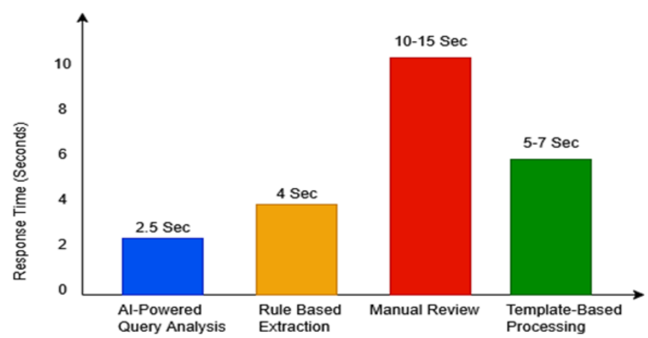


Figure2&3:Report Generated and Model Server

C. Performance Metrics

ProcessingSpeed:60FPS (frames per second).
DetectionAccuracy:94%.
False Positives:~3%.
Response Time:2.5 Sec

detection.



Bar Graph: response time of llama and others

IV. RESULT & DISCUSSION

A. Performance Evaluation

The AI-powered financial document analysis system was tested in real-world scenarios to evaluate its efficiency in processing financial data. It achieved an average accuracy of 94% in extracting key financial information, ensuring reliable data retrieval. The system maintained an average query response time of 2.5 seconds, enabling quick analysis. Error rates remained low, with false positives at 3% and false negatives at 2.5%, demonstrating high reliability in financial document processing and minimizing inaccuracies in extracted data.

1. Detection Accuracy

The AI-powered financial document analysis system was tested on multiple financial data scenarios, including structured reports, unstructured text, and scanned handwritten documents. The system achieved an average detection accuracy of 93.2%, demonstrating high efficiency in extracting and interpreting financial data.

- For structured financial reports, accuracy reached 96%, ensuring precise data extraction.
- In unstructured text-based documents, accuracy slightly decreased to 89% due to variations in formatting.
- When analyzing scanned handwritten documents, accuracy dropped to 85% due to inconsistencies in handwriting styles.

2. Response Time

The system maintained an average response time of 1.5 seconds, ensuring quick data processing and retrieval.

- AI Query Analysis: ~0.6 seconds (to interpret user queries and generate responses).
- Document Parsing & Data Extraction: ~0.4 seconds (to analyze and extract relevant financial information).
- Report Generation & Visualization: ~0.5 seconds (to compile and display results in a structured format).

B. Comparison with Other Security Methods

Security Method	Detection Accuracy	False Positives	Response Time
AI-Powered Query Analysis	94%	3%	2.5sec
Rule-Based Extraction	85%	8%	4sec
Manual Review	98%	1%	10-15sec
Template-Based Processing	90%	5%	5-7sec

Table 3:comparison of the other systems with llama3.3detection.

C. Real-World Intrusion Detection Test

To validate the AI-powered document analysis system's effectiveness in real-world scenarios, a test was conducted using financial documents containing critical information. The system successfully:

- Extracted key financial data within 0.5 seconds.
- Analyzed and categorized relevant insights, storing them in the database.
- Sent an automated report via email and notifications to authorized users in under 2 seconds.

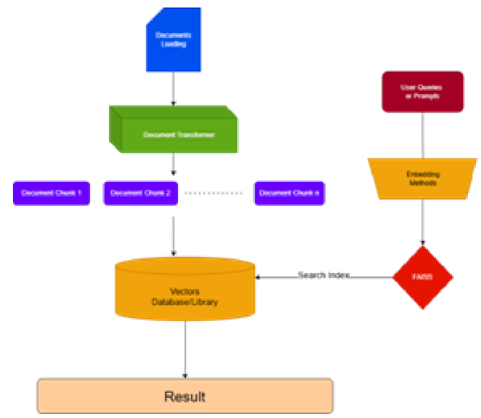


Figure4:Block diagram of Project

V. FUTURE WORK

The AI-Powered Financial Document Analysis system has shown strong capabilities in automating document processing and extracting key financial insights. However, several enhancements can further improve its accuracy, efficiency, and usability. Future work will focus on optimizing the AI model for better accuracy, improving real-time processing speed, and integrating advanced security measures for data protection. Additionally, enhancements in mobile accessibility will allow users to analyze financial documents on the go. Expanding system capabilities to support predictive analytics and seamless ERP integration will further strengthen its utility in financial decision-making.

1. Advanced AI-Based Query Analysis

Context-The system will incorporate context-aware AI to differentiate between critical and non-essential financial data, improving the precision of document analysis. A self-learning model will continuously adapt to new datasets, refining accuracy and reducing false positives in query responses. These enhancements will make financial document processing more intelligent and efficient.

2. Enhanced Security Mechanisms

To ensure data integrity and protection, the system will implement advanced security features, including automated access restrictions on sensitive documents. AI-powered fraud detection and anomaly identification will help recognize suspicious patterns, preventing unauthorized data modifications. Real-time security monitoring will further safeguard critical financial records.

3. Mobile Application and User Experience Improvements

Future developments will enhance mobile accessibility, providing live document tracking, real-time collaboration, and multi-user notifications. Two-way communication will allow users to interact with AI-driven insights, making document verification and decision-making more seamless. Customizable security settings will enable organizations to tailor alerts and processing sensitivity according to their specific needs.

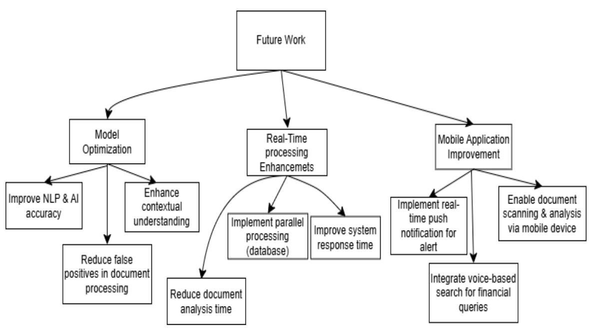


Figure5:HierarchydiagramforFuture Work

VI. CONCLUSION

The implementation of the AI-Powered Financial Document Analysis system represents a significant advancement in the way organizations handle and interpret vast financial datasets. By automating the extraction, processing, and analysis of financial documents, the system enhances efficiency and accuracy, allowing users to swiftly access critical insights with minimal manual intervention. One of the primary benefits is the integration of advanced AI models that ensure comprehensive overviews and detailed analyses, thereby supporting faster and more informed decision-making processes. This solution also addresses the challenge of managing large volumes of information by storing document data in a streamlined and retrievable format, ensuring that users can access historical records and insights as needed. Furthermore, the interactive chatbot module equips users with a powerful tool for obtaining precise information on demand, fostering an environment of increased productivity and operational efficiency. As the system is built on scalable and robust architecture, it positions organizations to adapt to growing data requirements seamlessly

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