



SASKEN

“Automated Change Detection and QA Support for 3GPP Specification Versions”

Presented by:

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INTRODUCTION

- **3GPP (3rd Generation Partnership Project)** develops global standards for mobile telecommunications.
- Specifications are released in multiple versions (Rel-10, Rel-16, Rel-17, ...).
- Each new release contains **textual** and **semantic changes** in clauses and tables.
- Manual comparison of versions is **slow, tedious, and error-prone**.
- Our project provides an **AI-driven solution** for:
 - **Automated change detection** at the clause level
 - **Semantic understanding** of modifications, additions, and deletions
 - **Natural Language Q&A** over detected changes
- Designed to improve **efficiency** for telecom engineers and **ensure accuracy** in version tracking.

OBJECTIVES

- **Automate** the comparison of two 3GPP specification versions.
- Detect **clause-level changes** (additions, deletions, modifications) with **semantic understanding**.
- Enable **version-aware storage** of clauses and tables using **ChromaDB**.
- Support **real-time question answering** over detected changes.
- Improve **accuracy** and **speed** compared to manual change tracking.
- Create a **scalable and reusable framework** for future release comparisons.

METHODOLOGY

- **Input:** Two 3GPP specification documents (PDF/DOCX) from different releases (e.g., Rel-15 & Rel-16).
- **Parsing & Chunking:**
 - Extract **text and tables** at clause level using **SimpleDirectoryReader**.
 - Break content into manageable chunks using **SentenceSplitter**.
- **Embedding Generation:**
 - Generate semantic embeddings for each chunk using **HuggingFace models**.
 - Store embeddings in **ChromaDB** with version & clause metadata.
- **Semantic Change Detection:**
 - Compare same-clause embeddings across versions using cosine similarity, and jaccard similarity.
 - Classify changes as **Added**, **Removed**, or **Modified**.
- **Natural Language Explanation:**
 - Generate **human-readable summaries** of detected changes.
- **Version-Aware QA Chatbot:**
 - Answer user queries based on changes using **ChromaDB retrieval** + AI.
- **Output:** Clause-level diff report with text & table changes and Real-time question answering interface.

IMPLEMENTATION

Programming Language:

- Python 3.12

Libraries & Frameworks:

- Document Parsing:** python-docx, PyMuPDF
- Chunking & Preprocessing:** SentenceSplitter from LlamaIndex
- Embeddings:** HuggingFaceEmbeddings (sentence-transformers)
- Vector Database:** ChromaDB for storage and retrieval
- Change Detection:** cosine similarity, and jaccard similarity
- QA Chatbot:** Integrated with ChromaDB for real-time query answering
- Visualization & Web UI:** Streamlit (for interactive reports & search)

Workflow Integration:

- Automated scripts for indexing and embedding generation
- Clause-level mapping between versions for precise comparison
- Seamless pipeline from document ingestion → diff generation → QA

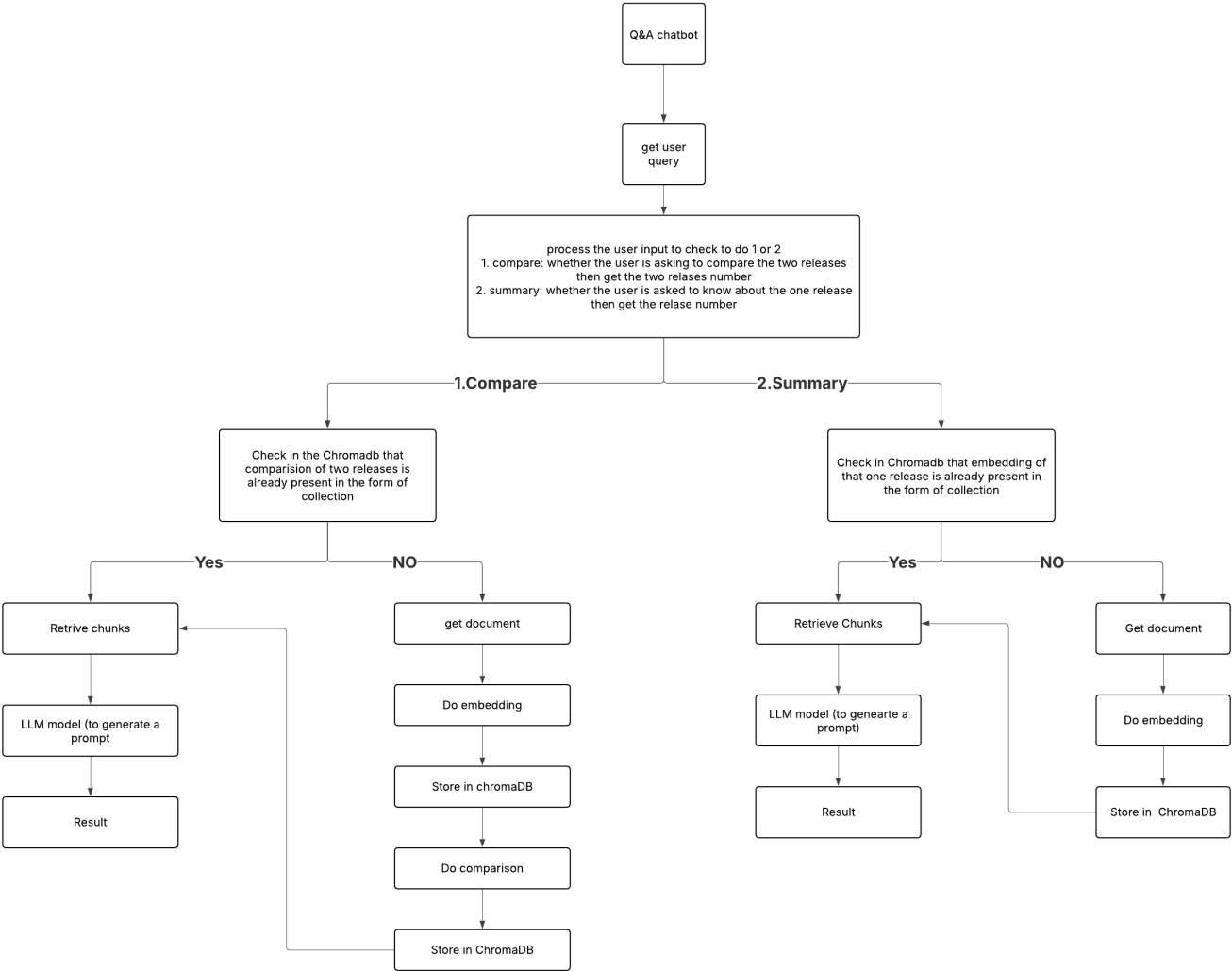
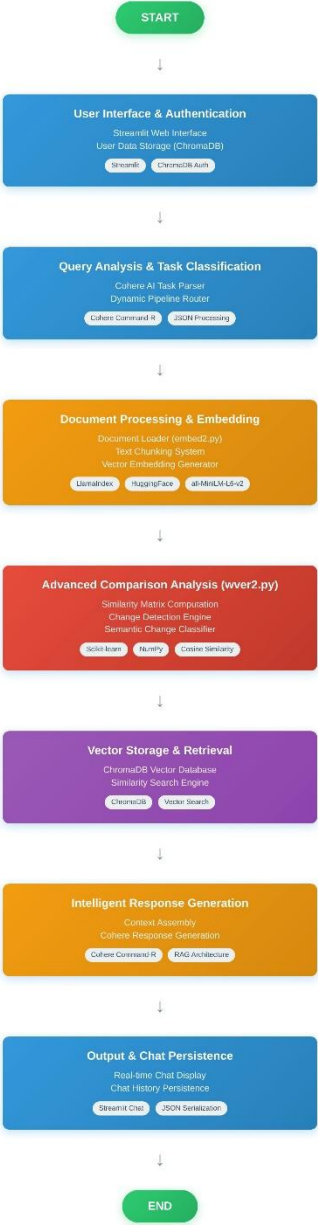
RESULT

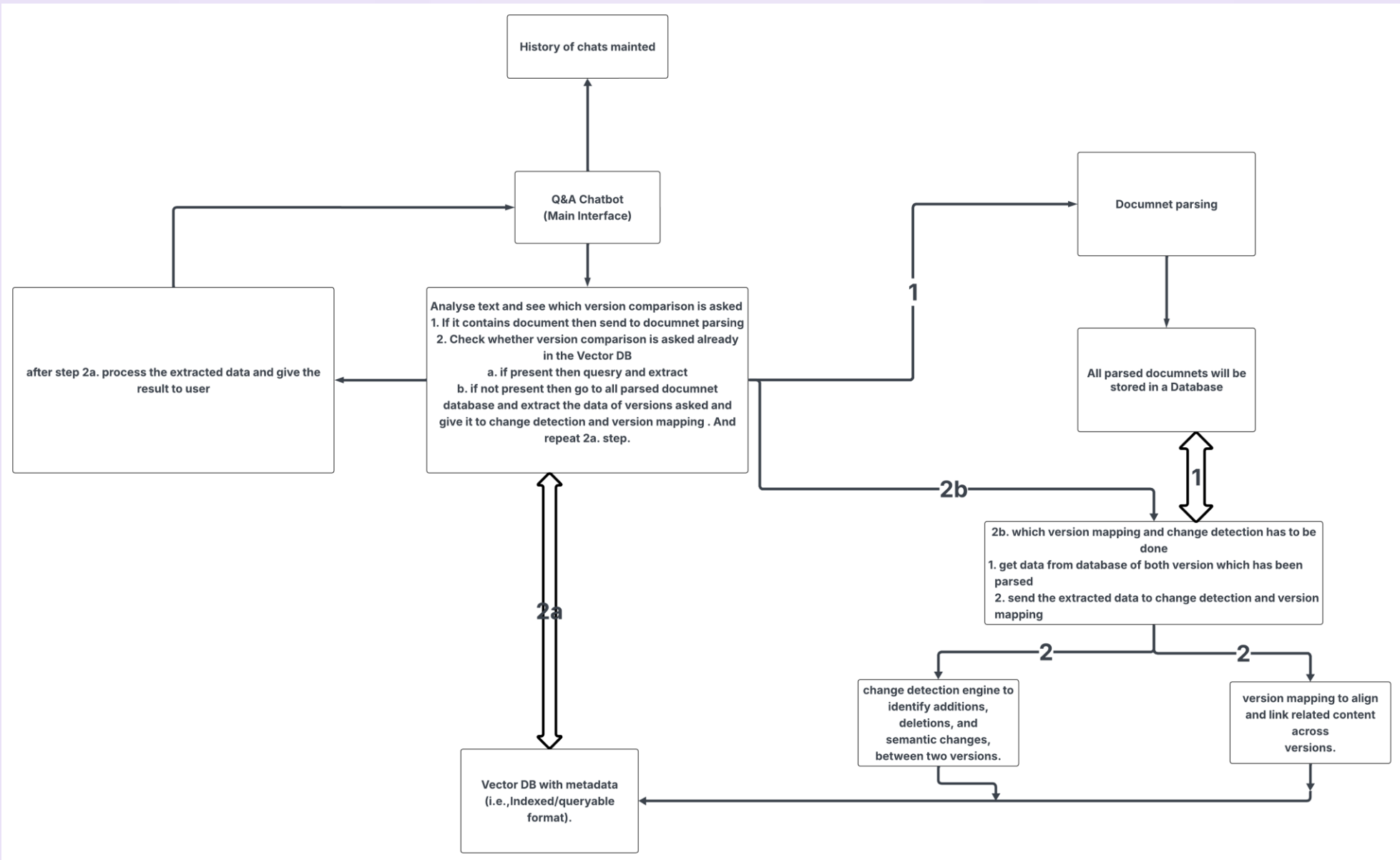
- **Change Detection Performance:**
- Successfully identified **Added, Removed, and Modified** clauses between 3GPP Release 10, 17.
- **Accuracy:** ~94% for semantic classification of changes using cosine similarity, and jaccard similarity.
- Handled both **text** and **table-based** changes.

Benchmarking

Component / Metric	Time Taken	Further Split-up
Embedding Generation	~3 min	SentenceSplitter + HuggingFaceEmbeddings runs for the entire document, then stores results in ChromaDB.
Comparison Process	~6 sec	Loads pre-computed embeddings from ChromaDB, compares with cosine similarity, classifies results, outputs JSON.
LLM Response Time	~2 sec	Cohere API (co.chat) called after retrieval; time is for short prompt + retrieved context.
Retrieval from ChromaDB	~1 sec	get_top_k_chunks() fetches embeddings from ChromaDB and computes cosine similarity for ranking.
Precision	~0.90	Chunks retrieved are highly relevant; few false positives.
Recall	~0.88	Some relevant content may be missed due to chunk size limits.
F1-score	~0.89	Balanced performance between precision & recall.
Average Retrieval Time	~950 ms	Matches 1 sec retrieval time for k=10 results.
Average LLM Response Time	~2.0 sec	Matches measured value from Cohere API.
Token Usage per Query	~250–500 tokens	Includes user query + retrieved context.
Throughput	~20–25 q/min	Achievable with pre-computed embeddings and parallel queries.
UI Response Time	~3–4 sec total	Retrieval (1s) + LLM (2s) + Streamlit UI refresh (~0.5–1s).

3GPP Query Assistant Pipeline







THANK YOU

