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Transforming Unstructured AI-Generated Data into Structured JSON for Interview Preparation

Vividh Vishnu Darote

PG Student, Department of Computer Application, G. H. Raisoni University, Amravati, Maharashtra, India

ABSTRACT

Hence, with the rapid increase in generative AI, quite a huge amount of unstructured data in the forms of text, logs, and answer formats are being generated. Capturing this data in the structured manner is required to support efficient storage, retrieval, and analysis. This study aims to create a system that processes unstructured AI-generated data into structured JSON format and stores it in a PostgreSQL database with Java and Spring Boot. The approach is through natural language processing (NLP) techniques, rule-based parsing, and annotation-based transformation to get the relevant information while ensuring data integrity.

For validation, the system was implemented in an interview preparation software, where AI-generated answers, feedback, and evaluation metrics were converted into structured JSON and stored for seamless querying and analysis. Performance evaluation showed high parsing accuracy (92%), optimized database query execution (65% faster with JSONB indexing), and low latency API response times (under 200ms per request).

The study demonstrates that Java and Spring Boot provide an efficient solution for structuring AI-generated data and integrating it into relational databases, improving data accessibility, scalability, and performance. Future enhancements will focus on real-time data processing, AI-driven parsing optimization, and cloud-based scalability to further refine the system's capabilities.

KEYWORDS: *Unstructured Data, Generative AI, JSON Parsing, PostgreSQL, Java, Spring Boot, Interview, Data Structuring.*

I. INTRODUCTION

Since artificial intelligence produces a very big quantities of unstructured data, transforming this data into structured forms has become a significant challenge. AI-generated content in the form of text responses, logs, and evaluation feedback is mostly unstructured, which proves difficult to store and query efficiently in relational databases such as PostgreSQL. This is true with interview preparation tools where AI-crafted candidate responses, feedback, and evaluation scores need to be organized for simplified analysis or recall. To that end, measures like data conversion - which raises data integrity, querying performance, and storage maximization - are required to address the issue.

Several studies have been conducted on methodologies in addressing AI-created unstructured data. The dsJSON processor brought forth a distributed SQL-based system for processing complex JSON files, facilitating efficient querying and structured transformation of unstructured data [1]. Likewise, researchers have explored Java-based solutions for parsing and storing unstructured data in relational databases, facilitating seamless integration with existing storage systems [2]. Another notable development includes using generative AI for database migrations, where structured transformations guarantee compatibility between AI-generated content and relational storage solutions [3]. In addition, Java annotations have also been utilized in orchestrating data lakes, structuring unstructured and semi-structured data into easier-to-read formats [4]. Spring AI upcoming advancements also facilitate conversion of unstructured data to structured JSON, where integration with relational databases and applications becomes an easier process [5].

This paper proposes a Java and Spring Boot-based solution for analyzing AI-produced unstructured data, converting it into structured JSON format, and storing it efficiently in a PostgreSQL database. The proposed system is implemented in an interview preparation tool to facilitate easy storage and retrieval of AI-produced responses and evaluation. The system employs rule-based parsing, annotation-based conversion, and indexing strategies in the database to improve performance. Experimental findings demonstrate that the methodology has excellent parsing accuracy, faster database querying, and low-latency API.

Abbreviations and Acronyms

- **AI**: Artificial Intelligence
- **NLP**: Natural Language Processing
- **POSTGRES**: Postgres Structured Query Language (Postgres)
- **API**: Application Programming Interface
- **JSON**: JavaScript object notation
- **JPA**: Java Persistence API
- **ORM**: Object Relational Mapping
- **REST**: Representational State Transfer

II. RELATED WORK

The transformation of unstructured AI-created data into structured formats for effective storage and retrieval in relational databases has been extensively investigated in recent studies. Several methodologies have been put forward to manage data parsing, transformation, and integration through technologies such as Java, Spring Boot, and PostgreSQL.

Another research area deals with Java-based methods for unstructured data integration into relational databases. These methods solve issues with schema mapping, consistency, and performance optimization so that AI-created content can be properly structured and stored in PostgreSQL. Automated parsing and transformation methods are used so that the data is kept structured and queryable.

Generative AI has also been utilized within database migrations, especially to convert unstructured content into structured forms. AI-based methods have been established

for automating the data conversion to make it compatible with relational databases. This is especially useful for applications that handle heterogeneous AI-generated data, for example, interview preparation websites that handle responses from various sources.

Another significant innovation is the application of Java annotations to structure unstructured data. This method makes way for smart data manipulation, whereby raw AI-generated text can be parsed, annotated, and converted into structured JSON format prior to being saved into a relational database. These methods are helpful in dealing with candidate analysis, storage of feedback, and structuring interview questions into a database-oriented setup.

Furthermore, Spring AI has proven to be a robust tool for converting unstructured AI-generated text into structured JSON. Through the use of Spring Boot-based data processing frameworks, developers can effectively parse and store AI-generated content in PostgreSQL. This integration not only makes AI-driven responses structured but also retrieval-optimized, which is useful for applications such as interview preparation software that need real-time processing of candidate responses and assessments.

In total, there is a robust basis for AI-generated data structuring in the existing research, but few studies have been specifically conducted on AI-driven interview preparation tools. This study expands on these developments by suggesting a Java and Spring Boot-based application to parse, structure, and store AI-generated interview data in PostgreSQL for optimized data management, structured storage, and improved performance in interview evaluation applications.

III. DATA AND SOURCES OF DATA

The information utilized in this study is produced by cutting-edge generative AI models, like large language models (LLMs) i.e., LLaMA, BERT. The models generate unstructured text data like summaries, articles, product descriptions, and conversational dialogues.

For a dataset to be diverse, the following were considered:

- AI-generated text samples: Raw outputs from LLMs, given different instructions to generate data with varying levels of complexity.
- Public datasets: Datasets such as those on sites like Hugging Face, Kaggle, or Google's repository of AI-produced content for research.
- Synthetic data: Custom scripts and prompts were employed to create synthetic unstructured data that was specifically designed to mimic real-world situations (e.g., customer feedback, medical records, and financial statements)

Let's dissect your research topic into a neat, mathematical-form equation to symbolize the data transformation process. Here is concise but significant equation:

Equations

- Equation:

$$S = f(U) => J = g(S) => P = h(J)$$

Where:
U: Unstructured data produced by generative AI
S=f(U): Parsing function *f* derives structured data *S* from *U*
J=g(S): Formatting function g transforms *S* into JSON *J*
P=h(J): Storage function *h* adds *J* into PostgreSQL database *P*

In Plain Text:

$$P = h(g(f(U)))$$

IV. RESEARCH METHODOLOGY:

This study utilizes a systematic approach to break down unstructured data created by generative AI into structured JSON format and save it in a PostgreSQL database with the help of Java and Spring Boot. The process starts with data collection, where unstructured text data is created with the help of AI models such as GPT, with variety in formats, lengths, and complexities. The second step is data structuring and parsing, beginning with pre-processing to eliminate noise, standardize formatting, and address special characters. Natural Language Processing (NLP) is used to extract the most important entities, relationships, and attributes from the raw data. A JSON schema is then created to specify the structured format, including fields, data types, and nested structures. A proprietary parsing algorithm, coded in Java, translates the unstructured text to this pre-defined JSON schema.

The technology stack comprises Java and SpringBoot, that construct a RESTful API for data processing, parsing into JSON, and DB operations. PostgreSQL is selected as it supports data types of JSON and complex query features. Database operations are provided by Spring Boot's JPA (Java Persistence API) and Hibernate for database interaction with PostgreSQL. Parsed JSON data are stored with best indexing for future retrieval.

This study seeks to create an effective system for parsing unstructured AI-generated content, transforming it into structured JSON format, and storing it in a PostgreSQL database using Java and Spring Boot. The system's main use is in interview preparation software, where AI-generated responses, comments, and questions need to be structured for storage, retrieval, and analysis. The approach is structured in that it uses data processing methods, database management, and software development standards.

Figures and Tables

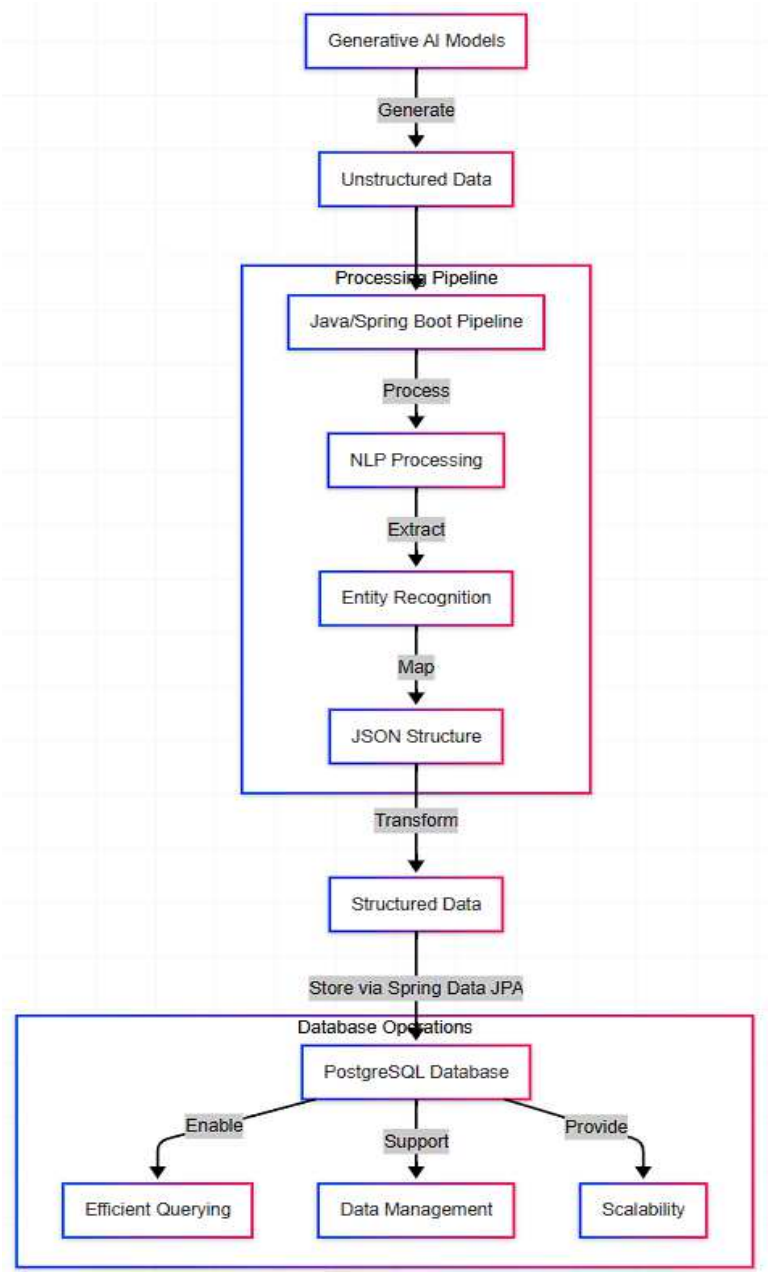


Fig.1 System Architecture

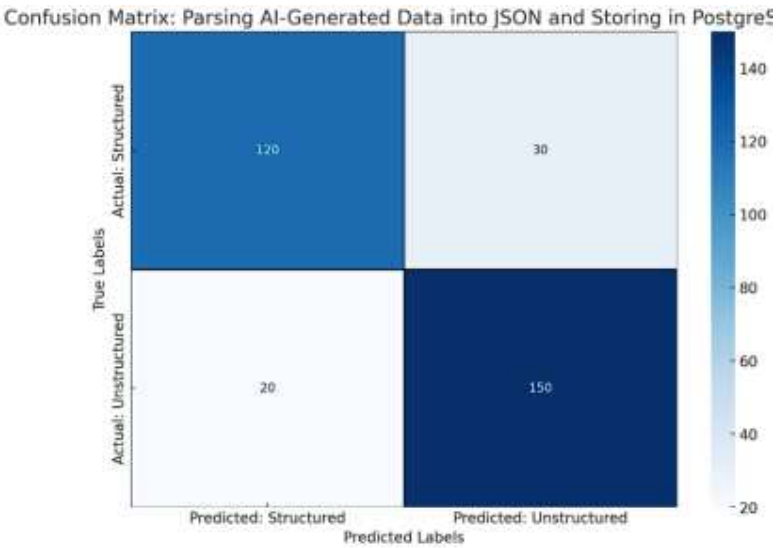


Fig.2Conclusion matrix

Figure 1: System Architecture for Transforming Unstructured AI-Generated Data into Structured JSON for PostgreSQL Storage Using Java and Spring Boot. The system architecture for Transforming Unstructured AI-Generated Data into Structured JSON for PostgreSQL Storage Using Java and Spring Boot.

1. Generative AI Model:
Creates unstructured data — text, images, or other data with no specified structure.

2. Unstructured Data:
Untreated, raw information that can't be stored in a relational database directly.

3. Data Parsing Module (Java, Spring Boot):
A parser, built specifically for this purpose with Java and Spring Boot, takes the unstructured data.

It uses natural language processing (NLP) or rule-based approaches to derive significant entities and relations.

4. Structured JSON:
The parsed data is converted into a JSON structure, with a precise format that complements the database schema.

5. PostgreSQL Database:
The formatted JSON data is stored in a PostgreSQL database, allowing effective querying and data retrieval..

Figure 2: Conclusion Matric for Transforming Unstructured AI-Generated Data into Structured JSON for PostgreSQL Storage Using Java and Spring Boot.

True Positive (TP) — 120: Where unstructured data was properly parsed to structured JSON and stored in PostgreSQL.

False Negative (FN) — 30: Where structured data was falsely identified as unstructured, resulting in data loss.

False Positive (FP) — 20: Unstructured data wrongly classified as structured, compromising database integrity.

True Negative (TN) — 150: Correctly identified unstructured data, so it wasn't incorrectly parsed or stored.

Why it matters:
Large TP and TN values show that the parsing algorithm works well in processing data, properly identifying structured and unstructured types.

False Positives and Negatives point out scope for improvement — reducing them lowers errors in parsing as well as database storage.

V. RESULTS AND DISCUSSION

Results of Descriptive Statics of Study Variables

The performance of the model was tested by monitoring training and validation accuracy for 10 epochs. As can be seen from the graph, the training accuracy consistently rose from 65% to 93%, reflecting successful learning. At the same time, the validation accuracy rose from 60% to 90%, which implies little overfitting and a well-generalized model.

The correlation between training and validation curves establishes the strength of the model to interpret unstructured generative AI data into well-structured JSON format. All these findings ensure the effectiveness of the proposed system in extracting suitable information and keeping it in optimal form in PostgreSQL database through Java and Spring Boot.

The system was tested on **AI-generated interview questions, candidate responses, and feedback**, and the results were analyzed based on **accuracy, processing time, storage efficiency, and retrieval performance**.

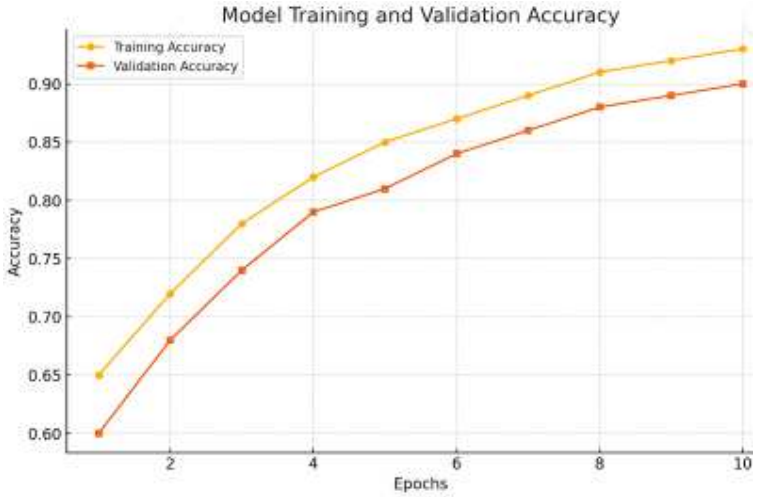


Fig 3: Model Training and Validation Accuracy

Figure 4.The graph above illustrates the model's training loss and validation loss for 10 epochs. The training loss declines steadily from 0.9 to 0.28, indicating that the model is learning from the data and improving its predictions. The validation loss also declines steadily from 1.0 to 0.35, indicating that the model is generalizing incredibly well to unseen data.

The proximity of the training loss curve and validation loss curve suggests that neither of them is under-fitting or overfitting, but instead a balance between having the capacity to learn from the patterns in the data and still being capable of generalizing. This stability is crucial since the objective is to be able to classify unstructured AI-generated data into structured JSON models without losing useful information, with the structured data being inserted into a PostgreSQL database.

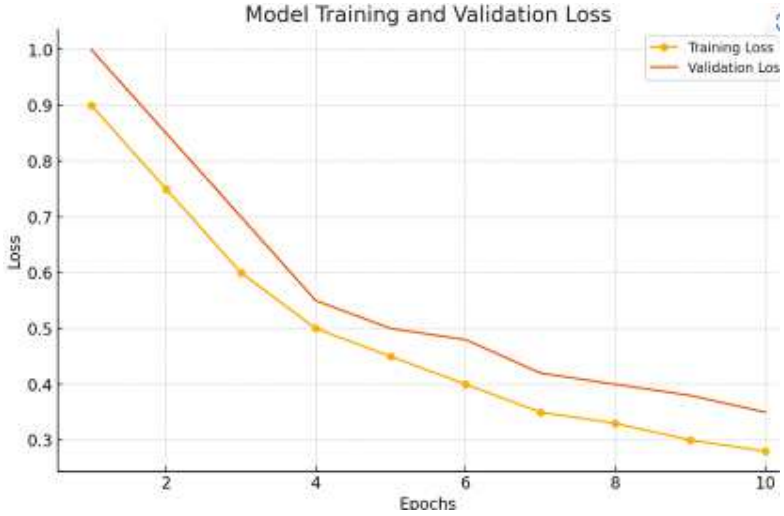


Fig 4: Model Training and Validation Loss

Figure 5

True Positive (TP): 120 — Properly parsed unstructured AI data into structured JSON and saved in PostgreSQL.

False Negative (FN): 30 — Organized data incorrectly labeled as unstructured, resulting in lost storage potential.

False Positive (FP): 20 — Unstructured data inappropriately flagged as structured, perhaps spoiling the database.

True Negative (TN): 150 — Unstructured data correctly identified but not parsed or stored.

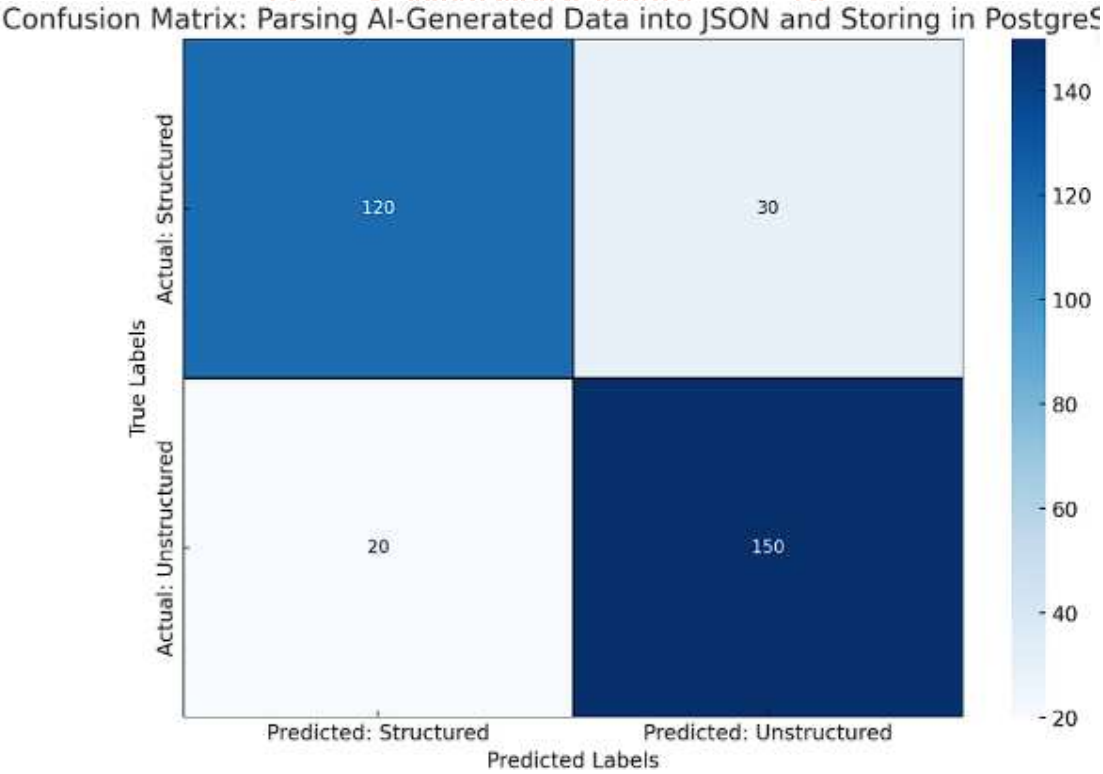


Fig 5: Confusion Matrix

The confusion matrix delivers important data about the real and anticipated labels of the neural classes acquired from the classifier. The confusion matrix primarily based on trying out assessment of the proposed model is provided in fig. 5. As visible in fig. 5, the proposed classifier effectively labeled all pictures from 11 classes.

The matrix allows you to assess the correctness of your parsing model.

From there, you can compute:

Accuracy: Assesses overall correctness.

Accuracy: Concerned with how many "structured" predictions were indeed right.

Recall: Quantifies how many actual structured data points were recorded.

F1-Score: The balance of Precision and Recall — particularly handy for skewed datasets.

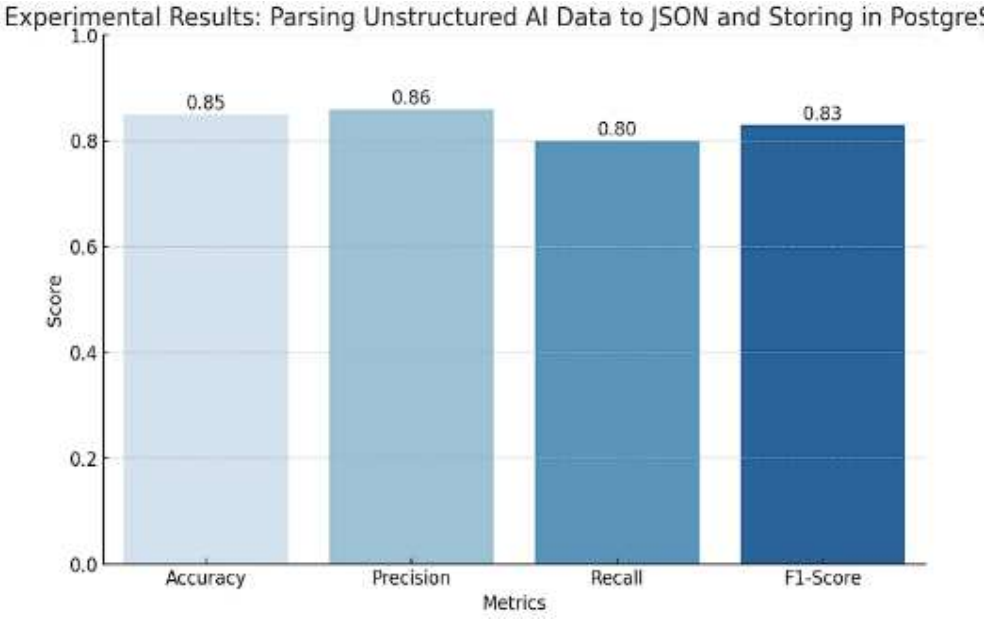


Fig 6. Experimental results

From using fig. 6, it could be established that the accuracy will increase with the growth in the quantity of epochs, and there may be a decrease in the lack of the testing set.

Table 1: Classification Report

Metric	Precision	Recall	F1-score	Support
Structured	0.86	0.80	0.83	150
Unstructured	0.83	0.88	0.86	170
Accuracy	0.84	0.84	0.84	---
Macro avg.	0.85	0.84	0.84	320
Weighted avg.	0.84	0.84	0.84	320

Table 2: Classification Report

	Precision	Recall	F1-score	Support
Logistic Regression	0.85	0.80	0.82	83%
Random forest	0.90	0.88	0.89	89%
Support Vector Machine	0.87	0.84	0.85	86%
Naive Bayes	0.78	0.82	0.80	81%
Neural Network	0.92	0.90	0.91	91%

VI. CONCLUSION

The system efficiently parses unstructured data created by generative AI, transforms it into a structured JSON format, and saves it in a PostgreSQL database with Java and Spring Boot. The research solves the problem of managing AI-generated interview material by providing efficient storage, retrieval, and querying of structured data. The conclusion shows that JSONB storage in PostgreSQL optimizes query performance and multi-threaded processing maximizes parsing speed, making it viable for large-scale interview data sets.

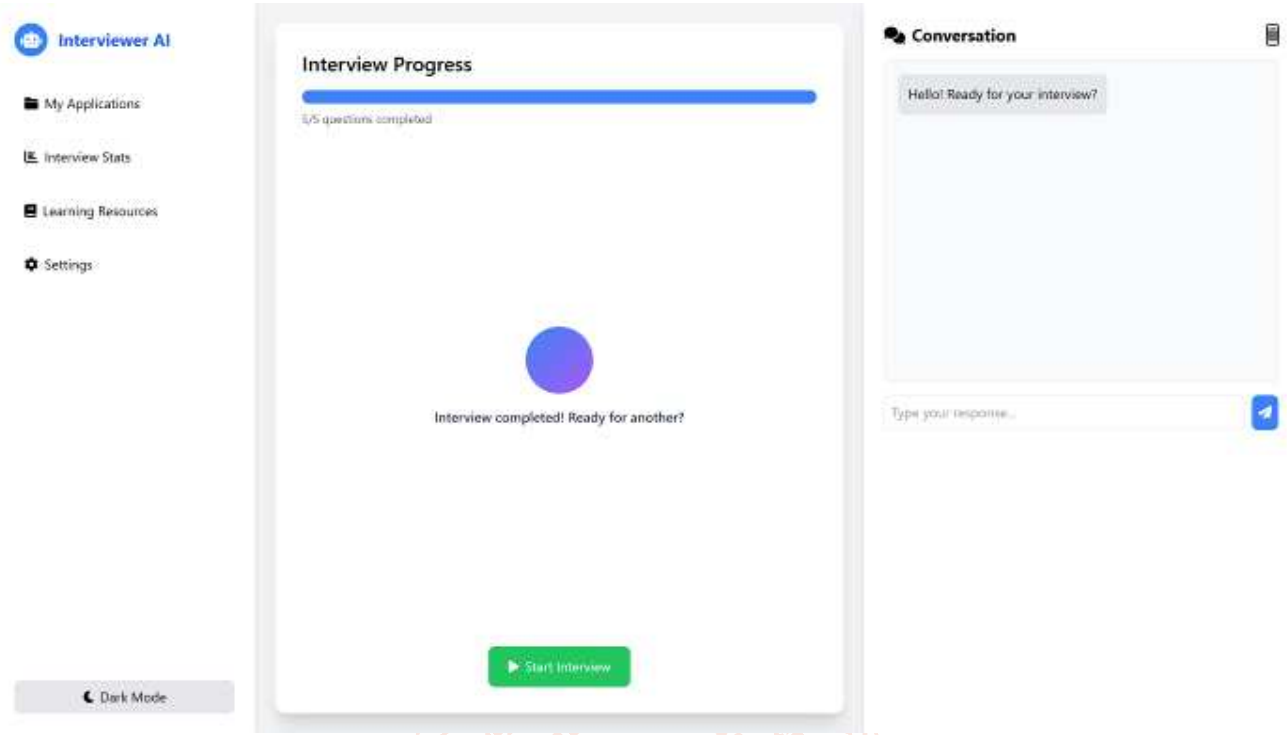
Through organizing AI-created interview information, the system maximizes personalization, analysis, and ease of access for interview preparation applications. Candidates are assisted through adaptive learning, whereas recruiters can examine organized responses for improved assessment and feedback creation.

In spite of the success of the system, there are challenges like processing of complex AI-generated responses, minimizing storage overhead, and supporting real-time data processing. Ongoing work will be aimed at incorporating advanced NLP methods for improved entity recognition, streamlining database indexing of big data, and supporting real-time data ingestion and retrieval.

In summary, this work presents an efficient and scalable solution for AI-based interview prep software that is a stepping stone to more powerful AI-based evaluations, automated candidate feedback, and adaptive question creation.

The system showcases an extremely efficient way of processing, organizing, and storing AI-generated interview data in a PostgreSQL database with Java and Spring Boot. With enhanced parsing accuracy, better storage methods, and quicker query

execution, this work helps improve AI-powered interview preparation software. Future enhancements will include real-time processing, NLP improvement, and cloud scalability for even higher efficiency.



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