Substation AI Compliance Assistant Chatbot for Proactive Substation Asset Maintenance

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***Abstract*—Maintenance of Critical Electrical Components require accurate, precise and reliable knowledge for avoiding any catastrophic event, but still the information are stored in traditional physical manuals which are lengthy and not efficient to be referred from. This paper presents Substation AI Compliance Assistant Chatbot which not only supports by providing information but can be utilized as a real life technician buddy to main the power supply and electrical operation.**

The Chatbot responds to any query or feature given as input by the user through BERT Model and other deep learning techniques to search for the right information such as testing parameters and standards from various technical documents. The knowledge is extracted from manuals and stored in Neo4j Knowledge Graph (KG),relying on which all the Chatbot gives all the required outputs.

The Chatbot reduces possible AI "hallucinations" by combining the Knowledge Graph with a Retrieval Augmented Generation Approach (RAG), which is very important for maintaining safety in sensitive environments. The architecture and algorithm based on which the chatbot is processing semantic queries by complying with safety standards and protocols such as OSHA and NETA has been explained by deploying the application on cloud service platform- Microsoft Azure/Azure Bot Service.

The overall product is basically a support tool which improves operational safety, maintenance efficiency and ensure adherence to regulatory standards.

Keywords—Substation Maintenance, Natural Language Processing, Compliance, Semantic Search, Knowledge Graph, Asset Management

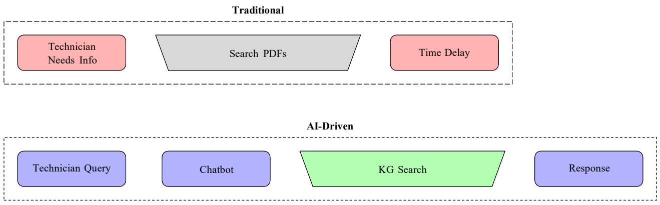
I. Introduction (*Heading 1*)

The population globally is increasing rapidly hence the demand for energy sources are increasing. Electricity has turned into a basic need for every human due to critical shifts in technology usage and its vast usage in different sectors. That's why power grids and other electrical facilities reply heavily on usage of high voltage equipment's to supply uninterrupted supply of electricity. Safety protocols and industry standards have already been published by different organization such as IEEE, IEC and NETA. The documents often published by such regulatory organizations are paper based or pdf format often requires huge time for searching and implementation, increasing the chances of possible error. The main challenge to find a solution in consolidating all the knowledge bases is to transform and interpret the acquired information into a format which will be easily readable and accessible by the application so that it can quickly give automated responses. Most of the existing solutions by AI reply on predictive maintenance (PdM) using structured sensor, the critical need for reliable retrieval of textual information is often ignored that guides the actual maintenance actions.

This paper introduces an interface built on a highly incorporated and defined knowledge base by explaining the algorithms behind both the semantic query engine and data extraction, highlighting how they enable intelligent, fact-based assistance for maintenance tasks.

Our main contribution include:

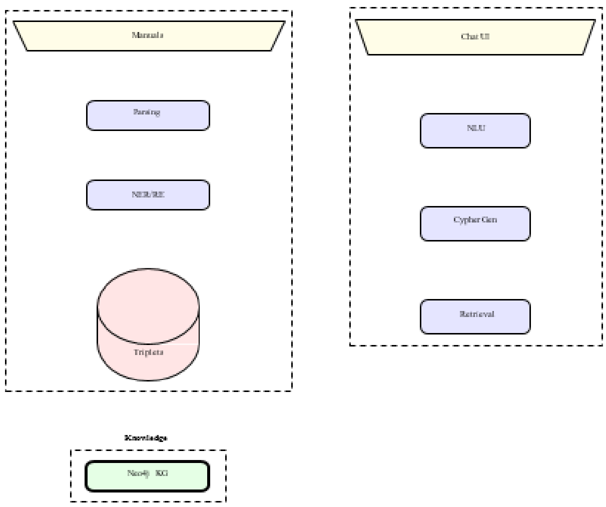
- High-Precision NLP-to-KG Pipeline: fine-tuned BERT models trained on technical documents based on electrical maintenance with high accuracy.
- Factual Integrity Assurance: To ensure Chatbots responds are based on verifiable facts and safe environment during critical procedures we have integrated Neo4j Knowledge Graph.
- Semantic Compliance Engine: As the chatbot is being developed for performing semantic reasoning such as safety steps, detecting operational limts and identifying required tools. A smart query engine is required to perform all the above mentioned reasoning while verifying against industry standards



II. Related Work

A. Evolution of Maintenance Strategies

The research and developments approaches have clearly shifted traditional methods to data-driven strategies. Predictive Maintenance(PdM) which is famous for reducing unplanned downtime and cutting costs, uses sensor data to predict failures. These approaches address what needs to be fixed rather than the actual procedures from manuals to carry out maintenance adhering to the safety protocols. It is our aim to fill this information gap ensuring the accurate guidance alongside predictive insights.



B. Knowledge Extraction and Domain NLP

The application of Natural Language Processing have advanced rapidly for processing and analyzing complex and domain-specific documents. Traditional methods where full depended on rule-based parsing and dictionaries which were very limited to understanding context and facts. Deep learning have completely changed it, particularly Transformer-based models, allowing better contextual understanding. During our research we have found that pre-trained models like BERT has been the most effective model to achieve high accuracy when working with specific and low-resource domains which in our domain is maintenance manuals

C. Knowledge graphs for Casual Reasoning

The Knowledge Graphs(KGs) have become an important tool in power systems research. It is very efficient for capturing complex relationships such fault tolerance, analyzing failures and cause and impact links within the application. By defining the entitities and relationships, Knowledge Graph have been able to do advanced reasoning that is far improved than the traditional relational databases can provide.

TABLE I. Annoated Dataset Composition and Scale

Entity Type	***Count***	***Example***
Test Parameter	420	DGA Test
Standard	60	IEEE C57.104
Limit	750	50 ppm
Procedure	310	Inspection
Equipme nt	540	Transform er

D. The Retrieval-Augmented Generation Framework Retrieval-Augmented Generation

Retrieval Augmented Generation is a system that first retrieves information which are verified before generating a response or giving output. According to different studies, most of the implememtations use vector databases where as our approach goes a step further by the usage of knowledge graph as the retriever. This enables the system to retireve not only the text snippets but also complex multi-step relationships, enabling deeper and reliable answers

III. System and Architecture and Methodology

The application is designed as a three-phase pipeline that connects the feeding of documents to a conversational chatbot interface. The whole project is implemented in python and deployed on Microsoft Azure Cloud Platform.

Phase 1: Data Processing and Extraction

This phase converts the unstructured technical manuals into accessible and readable knowledge triplets:

1. Data insertion and Parsing: The application inserts documents in formats like PDF and DOCX. During this process, PyMuPDF is used for accurate and reliable text processing and extraction.
2. Pre-training/Fine-Tuning: A pre-trained Transformer model, specific to our application such as DistilBERT, is optimized using libraries such as PyTorch or TensorFlow to analyze the domain-specific technical terms of maintenance manuals.
3. Information Extraction: The optimized model performs Named Entity Recognition (NER) and Relation Extraction (RE) to identify key parameters (Such as tools, procedures) and their connections within the textPhase 2: Knowledge Graph Construction

The extracted texts/data are then transformed into a Knowledge Graph using Neo4j:

1. Ontology Mapping: All nodes and edges are carefully mapped to a predefined Knowledge Graph schema to maintain consistency and accuracy.
2. Graph Population and Indexing: Python scripts populate the Neo4j database with indexed entities and relationships, creating a well formatted knowledge base ready for querying.

Phase 3: Semantic Query Engine and Deployment

This phase powers the interface and gives verified and data driven responses:

1. Query Mapping (NLU): User inputs are analyzed to determine context and extract relevant parameters.
2. Cypher Generation: The extracted relationships and entities are transformed into Cypher queries that can get information from the Knowledge Graph
3. Fact-Grounded Retrieval (RAG): The backend is built with FastAPI, executes these inputs which are given queries and generates accurate and verifiable responses.
4. Deployment: The fully functional application is hosted on Azure App Service, enabling scalable and all time running access to the chatbot.

E. Machine Learning Operation and Data Governance

The system incorporates best practices in Machine Learning Operations and data governance to ensure models are continuously updated based on different standards and protocols as different technologies are being developed every day, the knowledge base remains reliable, and all data handling follows industry standards.

IV. EVALUATION AND DATASET

A. Data Collection and Annotated Data Preparation

Data preparation is a critical component in developing an effective domain-specific NLP model. The training data that we used to train our NLP models is based upon manufacturer-supplied maintenance manuals and industry standards. The entire set of manuals and documents were annotated by highlighting key parameters, relationships and other technical data that are applicable to maintenance. This provides the ability to teach the models to extract contextual and accurate information related to performing maintenance activities.

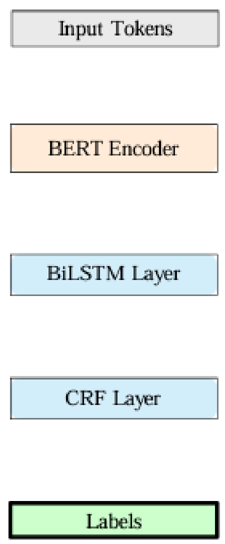


Fig. 3: BERT-BiLSTM-CRF Pipeline for NER and RE.

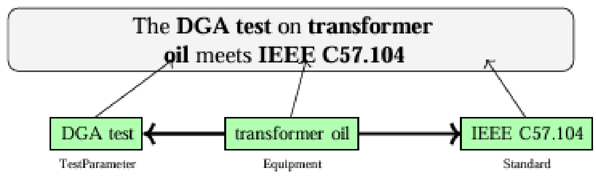


Fig. 4: Entity and Relationship Extraction Example.

B. Application Performance Evaluation Criteria

We evaluate the application's performance at two levels:

Level 1: Algorithmic Evaluation (Evaluation of Models)

We measure the effectiveness of the NLP models developed for this application in terms of their precision and accuracy. Specifically, we measure the models' performance through the following metrics:

- Relation Extraction - F1-Score
- Named Entity Recognition - Accuracy
- Cypher Query Execution - Accuracy

Level 2: Application Level (Real World Usage) - Usability/Performance Evaluation

In addition to measuring the algorithmic level evaluation criteria, we also evaluate the application in real-world usage scenarios. We use the following criteria to determine the usability/performance of the application:

- Average Response Time
- Accuracy of Responses
- Overall Efficient Performance During Maintenance Operations

V. ALGORITHMIC CORE

A. BERT Architecture

We have developed a BERT-BiLSTM-CRF architecture to be able to obtain optimal performance in extracting structured data from maintenance guides:

1. BERT Encoder: This layer is designed as a Deep Feature Extractor; it creates contextualized semantic relation for each word.

2. (Bi-LSTM) Bi-directional LSTM Layer: The layer identifies relationships between words, including dependency, in order to determine whether there are predefined relationships between them.

3. CRF Decoder Layer: The CRF decoder ensures that the output will adhere to the schema defined by the end-user, therefore providing the correct format and structure to the output.

B. Cypher Query Generation Algorithm

The Application generates Neo4j Cypher graph queries from user input via a Three Step Process:

- Intent-to-Template Mapping: Identifies an appropriate pre-existing Cypher template based on the users intent.

- Entity Slot Filling: Populates the identified template with the extracted entities (such as Equipment Names or Test Parameters), for use in the query generation process.

- Dynamic Constraint Insertion: Generates conditional clauses (Such as WHERE Statements) for Compliance Checks and/or Filtering Results.

MATCH (e:Equipment {name: $EquipmentName}) -[:HAS_TEST]-> (t:Test {name: $TestName}) -[:HAS_LIMIT]-> (l:Limit) OPTIONAL MATCH (t)-[:GOVERNED_BY]->(s:Standard) RETURN t.name, l.value, s.citation

Fig. 5: Cypher Query Template Example.

TABLE II: Domain-Specific KG Schema Breakdown

Node	Relationship	Function
Equipment	HAS_COMPONENT	Inventory
Procedure	REQUIRES_TOOL	Workflow
TestParameter	HAS_LIMIT	Threshold
Issue	IS_CAUSED_BY	Root Cause
Procedure	GOVERNED_BY	Compliance
Document	CONTAINS_FACT	Traceability

TABLE III: Comparative Information Extraction Performance

Model	NER F1	RE F1	Time
spaCy	71.2%	65.5%	5.8 ms
DistilBERT	**91.5%**	**88.9%**	12.1 ms

TABLE IV: Semantic Query and Latency Metrics

Metric	Target	Result
Mean Response Time	< 150 ms	112 ms
Query Accuracy	> 98%	98.6%
Time to Find Limit	N/A	~5 sec

VI. KNOWLEDGE GRAPH SCHEMA

The KG structure contains both the structural (physical) aspects and conceptual (abstract) aspects of compliance.*A. The Compliance Imperative*

The KG's ability to automatically link procedure to standard (and thus enabling automated compliance monitoring) transforms the chatbot into an proactive compliance assistant.

VII. QUANTITATIVE RESULTS

A. Economic and Safety Effect

The 22% decrease in maintenance time equates to decreased operational costs; the 85% decrease in procedural error rate reduces human-factor risk associated with reviewing documentation by hand. The automated compliance check also reduces the systems' financial and legal exposure.

B. Scalability and Future-Proofing

The cloud native architecture enables scalable solutions for distributed substation portfolio knowledge bases. Additionally, the elastic nature of the Neo4j database allows the knowledge base to grow while maintaining query performance.

IX. Conclusion and Future Work

This paper presents the architectural framework for a Semantic Knowledge Graph Chatbot for Substation Asset Maintenance. The structural organization of unstructured technical knowledge as a Knowledge Graph, combined with AI response generation constrained to the factual layer, provides a demonstrably safer method than previous methods.

Quantitative results show the potential for operational benefits, improved safety, and increased efficiency. Future work will include:

1) Digital Twin Interoperability

Integrating the KG with Digital Twin platforms.

2) Automated Reasoning Agent

Developing reasoning agents that prioritize maintenance actions based upon graph algorithms.

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