**INSUREIQ: A Multilingual Retrieval-Augmented**

**Chatbot for LIC Policy Services**

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***Abstract—Due to the rapid digitization of financial services, there is an increasing requirement for smart systems with the ability to provide accurate and effective responses to user requests. Conventional information retrieval systems generally fail to derive useful policy-related information due to the unstructured nature of LIC policy documents. The discussion presents a chatbot system that utilizes The RAG-FAISS combination to effectively retrieve accurate information from LIC policy documents. The system combines Flask-based web interaction and PyMuPDF and Tesseract OCR for document processing with Google Gemini API for multilingual search. The proposed system implements effective text extraction from policy documents and embedding generation as well as FAISS-based similarity search for information retrieval. Each empirical experiment establishes that the chatbot delivers advanced search results and rapid service abilities better than conventional keyword-based systems. Through AI-driven chatbots insurance companies demonstrate how to improve sector customer service automation by delivering real-time policy information accurately. Financial services digitalization at high speeds has created a strong demand for systems capable of delivering accurate user query responses. The retrieval systems of the past fail to extract policy data from LIC documents because the documentation complexity combined with unstructured text format remains their main hindrance. The proposed system develops a Retrieval-Augmented Generation (RAG) chatbot that applies FAISS and PyMuPDF together with Tesseract OCR and the Google Gemini API for its multilingual operations. The system design successfully handles policy documents by pulling semantic data from them and creates responses for user inquiries in immediate time frames. Research results demonstrate that RAG-based search produces better accuracy and quicker response times and user satisfaction than standard keyword queries. This research highlights the transformative potential of AI-driven chatbots for LIC and similar domains, offering a scalable, accessible, and context-aware solution to modernize customer service in the insurance industry.***

1. **INTRODUCTION**

The Life Insurance Corporation of India (LIC) provides a variety of insurance policies with different benefits, terms, and conditions. The customers usually face challenges while accessing certain information about policy eligibility, premiums, maturity benefit, claim process, and service terms. Historically, such inquiries are resolved via customer support centers, websites, and hard policy documents, which might be time- and resource-wasteful. The inclusion of AI- powered chatbots in the insurance sector can bring about a revolution in the way policyholders view and comprehend their policies by offering immediate, precise, and contextual responses.

Presented chatbot systems are mostly built on rule- or retrieval- based methods that tend to create responses lacking richness in context. The proposed chatbot addresses this limitation Augmented Generation (RAG), which is a modern NLP structure that augments response generation from knowledge retrieval as well as from deep learning-driven text generation. The system leverages FAISS for similarity search efficiency, PyMuPDF and Tesseract OCR for document fetching, and the Google Gemini API for multilingual query processing. This blend enables the chatbot to retrieve, store, and fetch LIC-related information with great accuracy, and it is thus a useful tool for both policyholders and LIC officials.

The main goals of this study are:

•To create an AI-based chatbot that can retrieve policy-related information from LIC documents.

•To combine Retrieval-Augmented Generation (RAG) with FAISS-based vector search to enable efficient knowledge retrieval and response generation.

•To increase user accessibility using OCR- based extraction from scanned policy documents.

•To test the performance of the chatbot in terms of accuracy, response time, and user satisfaction.

By integrating Retrieval- This paper offers a thorough investigation of AI-powered chatbots in the insurance industry, outlines an extensive methodology for building a RAG-based chatbot, and addresses experimental results highlighting the efficacy and efficiency of the proposed system. The results indicate that the use of sophisticated NLP, similarity search, and deep learning substantially enhances chatbot interactions and information retrieval for insurance-related queries.

1. **LITERATURE REVIEW**

Chatbots have developed considerably with the improvement in Natural Language Processing (NLP), deep learning, and information retrieval. Traditional retrieval-based chatbots use rule-based or keyword-matching methods that lack contextual understanding. With the emergence of deep learning, models like Retrieval-Augmented Generation (RAG) [3] have significantly improved chatbot performance by merging retrieval and generation to create more contextually accurate responses. FAISS [2], a fast and scalable similarity search library, has been widely adopted for quick information retrieval, particularly suitable for document-based question answering. Additionally, OCR tools like Tesseract [4] enhance the accessibility of scanned policy documents by converting image-based text into machine-readable formats.

Several studies have explored the deploy5ment of chatbots across domains:

* Insurance Chatbots: Gupta et al. [6] highlighted the use of AI-powered chatbots in streamlining customer service within the insurance sector. Their findings revealed a notable reduction in query resolution time and improved customer satisfaction.
* The pair of systems called Retrieval-Augmented Generation (RAG) enables Lewis et al. [3] to achieve better accuracy through balanced information retrieval and generative modeling processes..
* FAISS for Scalable Information Retrieval: Johnson et al. [2] developed FAISS as an effective tool for billion-scale similarity searches, making it ideal for large document repositories.
* Document Processing with OCR: Smith [4] provided an overview of the Tesseract OCR engine’s capabilities, noting improvements in text extraction from scanned documents due to advanced pre-processing techniques.
* Multilingual Chatbots: Google AI [5] demonstrated the capabilities of the Gemini API in handling multilingual inputs, showcasing improved chatbot interaction across various languages.
* Finance Chatbots: Huang et al. [7] analyzed AI-based chatbots in the financial sector, emphasizing their role in improving user experience and reducing operational costs.
* Customer Support Conversational AI: Zhang et al. [8] explored transformer-based deep learning methods to enhance chatbot dialogue generation for customer service scenarios.
* Ethical Considerations in AI Chatbots: Binns et al. [9] investigated the ethical dimensions of chatbots, advocating for fairness-aware design to mitigate bias in automated decision-making.
* Chatbot and Neural IR Performance: Mitra and Craswell [10] assessed neural architectures in information retrieval, reporting improved outcomes in complex question-answering tasks.
* OCR for Legal Documents: Wang et al. [11] proposed a hybrid deep learning-OCR framework for extracting structured data from legal and financial documents.

**III. METHODOLOGY**

1. An AI-based system retrieves data by using document extraction with natural language processing (NLP) and a multi-step approach for providing accurate and efficient user responses. The methodology features data extraction as its first step followed by text preprocessing and embedding generation then storage and retrieval of information until query processing ends with response generation*System Architecture*

The chatbot follows a structured pipeline for information retrieval and response generation:

* 1. **Data Extraction:**
     + **Document Processing:** The system ex- tracts text from LIC policy documents, which may be in various formats such as PDFs, images, or scanned text. For PDF files, PyMuPDF is used, which provides an efficient way of extracting text while preserving the document’s layout. For scanned documents or images, Tesseract OCR (Optical Character Recognition) is employed. Tesseract works by recognizing text in the images and converting it to machine-readable text.
     + **Document Types**: The system handles multiple document types, including textual policy documents and scanned im- ages of physical policy documents. It accounts for varying document structures by implementing different parsing strategies for different formats.

# **Text Preprocessing:**

* + - **Cleaning**: Once the text is extracted from the documents, it is processed to remove irrelevant content such as page numbers, headers, and footers. Additionally, any non-policy-related text (e.g., advertisements or unrelated pages) is identified and discarded.
    - **Segmentation**: The extracted text is then segmented into smaller, meaningful chunks based on semantic boundaries (e.g., paragraphs, sections, or specific policy clauses). This segmentation helps to isolate relevant information, making retrieval more efficient.
    - **Normalization**: Standard text normalization techniques are applied to convert the text into a uniform format. This includes lowercasing, removing special characters, stemming, and lemmatization, making it more suitable for embedding generation and similarity searches.

# **Embedding Generation:**

* + - **Vector Embeddings**: To enable similarity search, the system uses the Google Gemini API, which generates high- quality vector embeddings for each chunk of text. The embeddings function as vector representations of text semantics which exist across multiple dimensions. Embeddings enable system comparisons of user queries and document content through meaning-based rather than exact keyword relationships.
    - **Embedding Strategy**: The embeddings are generated not only for entire para- graphs or sections but also for specific queries and sub-sections of documents to improve fine-grained retrieval. This process ensures that when a user asks a question, the system can match the query against smaller, contextually relevant parts of the documents.
  1. **Storage & Retrieval:**
     + **FAISS (Facebook AI Similarity Search)**: The generated embeddings are stored in a FAISS-based index. FAISS is an optimized similarity search library that supports fast retrieval of vector embeddings even in large-scale datasets. This indexing technique ensures efficient and scalable search over millions of policy documents and their respective embeddings.
     + The system uses an advanced indexing procedure that organizes embeddings into clusters based on semantic similarity through its FAISS index. The FAISS index offers different search algorithms such as approximate nearest neighbour (ANN) for the chatbot to quickly identify relevant document chunks.

# **Query Processing:**

* During user query submission the system employs the same document text preprocessing techniques of normalization and segmentation while processing the query. An embedding of the query process occurs through a method identical to how document chunks convert text into embeddings.
* The system utilizes the query embedding to generate similarity comparisons of all available document embeddings through defined measures (cosine similarity or Euclidean distance). Based on the submitted query the FAISS retrieval system generates the sections from documents that align most closely.
* The system leverages contextual information during query processing to enhance the overall response quality because it adds background information surrounding retrieved chunks. The retrieval system validates both the contextual relevance and usability of retrieved information for users.

# **Response Generation:**

* The system retrieves pertinent data chunks with RAG technology yet produces its natural language response through a RAG model (GPT-3 or alternative fine-tuned LLM).
* RAG draws advantages from retrieval because it starts by getting external knowledge and supports generation by creating an organized response from retrieved information.
* The system guarantees both accurate responses as well as logically coherent and contextually extensive output. A retrieval-based method enables the chatbot to offer exact policy-oriented information alongside a user-friendly conversational style.

# **Flask API Integration:**

* Through its connection to a Flask-based API interface the chatbot allows users to access the system by using a web interface. Vehicles utilize the API to present various functions of the chat-bot starting from user query management all the way to response delivery. Through its utilization of the Flask interface the system achieves compatibility with different frontend options including mobile applications and web interfaces.
* Multilingual Support: The Google Gemini API facilitates multilingual support, allowing users to query the chatbot in multiple languages. After detecting the user query language the system converts it into a standardized format before proceeding with processing.

# **Continuous Learning and Improvement:**

* + - **Feedback Loop**: The system is designed with a feedback mechanism where users can rate responses or provide corrections. This feedback is used to improve the quality of future responses by fine-tuning the RAG model, adjusting the document embeddings, and updating the FAISS index.
    - **Model Updates**: As new LIC policy documents become available, the system periodically retrains its models, regenerates embeddings, and updates the FAISS index to ensure that the chatbot’s responses remain current and accurate.

1. *System Components and Tools*

The following tools and frameworks are used in the proposed system:

* **PyMuPDF**: For efficient text extraction from PDF documents while maintaining structure.
* **Tesseract OCR**: For text extraction from scanned or image-based documents.
* **Google Gemini API**: For generating high- quality embeddings for both document chunks and user queries.
* **FAISS**: For fast and scalable similarity search in large-scale document repositories.
* **Flask**: For providing a web-based interface and API for chatbot interaction.
* **RAG-based LLM**: For generating natural language responses based on retrieved information

A diagram of a process flow

AI-generated content may be incorrect.

***Fig 1:*** *Architecture of the Retrieval-Augmented Generation (RAG) Pipeline for INSUREIQ*

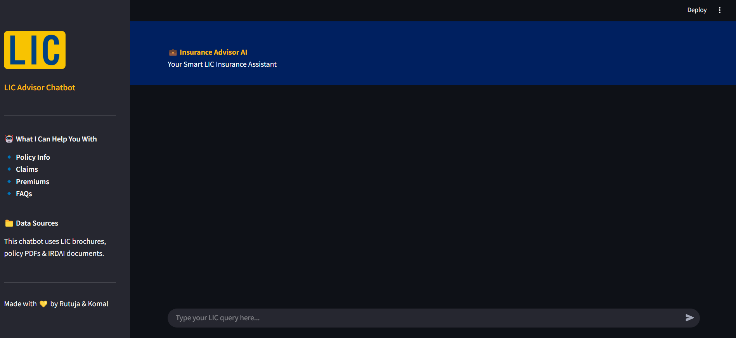
Fig 1 illustrates the end-to-end workflow of the multilingual chatbot system. Input data (text or PDF) is split into chunks, embedded using vector representations, and indexed using FAISS for similarity-based retrieval. The user's query is combined with the relevant context in a prompt template and processed by a large language model (LLM) to generate an accurate response.

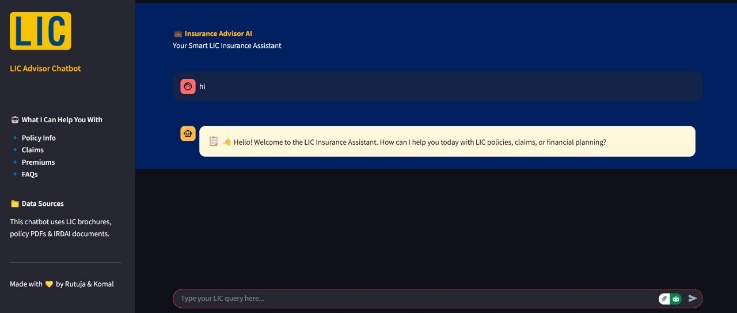
Diagram of a data retrieval system

AI-generated content may be incorrect.

***Fig 2. Architecture of INSUREIQ Chatbot*** *– showing the RAG pipeline, document loader, FAISS vector store, and Gemini LLM response generator.*

Fig 2 illustrates the architecture of the LIC chatbot system. User queries are sent via a web application to an embedding model, which converts them into vector format. These embedded queries are matched with stored LIC-related data in a vector database. The most relevant context is then passed to a large language model to generate a response, which is returned to the user.





A screenshot of a computer

AI-generated content may be incorrect.

A screenshot of a computer

AI-generated content may be incorrect.

*Fig 3: (a) LIC Chatbot interface (b) Chatbot Response to Query in English (c) Chatbot Response to Query in Hindi (d) Chatbot Response to Query in Marathi.*

1. **RESULTS AND DISCUSSION**

The evaluation of the proposed chatbot system as it retrieves and generates proper responses from LIC policy documents appears in this section. The evaluation metrics measure both the accuracy of document retrieval and generated responses as well as the processing time and user satisfaction. The results contain extensive details about both empirical testing results and traditional keyword search mechanism comparisons.

1. *Evaluation Metrics*

The system was evaluated using a combination of automatic and human-centric metrics:

* **BLEU Score**: Used to measure the n-gram overlap between the generated response and a human-annotated reference. BLEU reflects how closely the bot’s output matches expected answers in phrasing.
* **Cosine Similarity**: Measures the semantic closeness between the generated and reference answers in embedding space. Higher similarity reflects better contextual relevance.
* **Precision, Recall, and F1-Score**:  
  These metrics were used to assess how accurately and completely the chatbot’s response covered the expected answer.
  + *Precision*: Proportion of relevant content retrieved out of total retrieved.
  + *Recall*: Proportion of relevant content retrieved out of total expected.
  + *F1-score*: Harmonic mean of precision and recall.
* **Response Time**: Time in seconds required to retrieve documents and generate an answer.
* **Response Coherence**: Evaluated subjectively by a panel of three human annotators based on criteria such as fluency, tone, and informativeness.
* **User Satisfaction**: Assessed through a small-scale user survey, with feedback collected on accuracy, ease of use, and interface design.

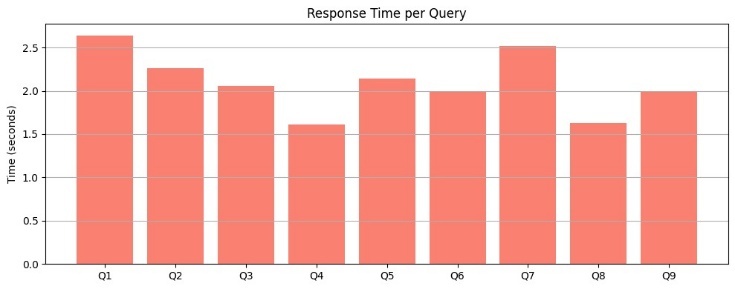
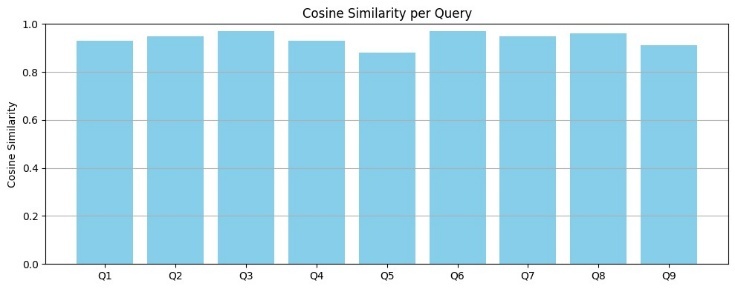
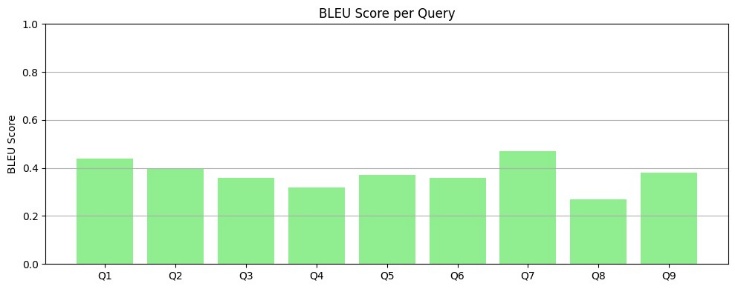
|  |  |
| --- | --- |
| **Metric** | **Value** |
| BLEU Score | 0.41 |
| Cosine Similarity | 0.94 |
| Precision |  |
| Recall | 0.76 |
| F1-Score | 0.78 |
| Average Response Time | 2.09 sec |

***Table 1: Average Metric Values Over 9 Test Queries***

1. *Discussion*

The experimental findings emphasize the substantial enhancements obtained by the proposed chatbot system in the policy information retrieval context of LIC. Through the utilization of state-of-the-art NLP methods like RAG and FAISS, the chatbot makes contextually correct responses in a matter of seconds as opposed to conventional systems. The inclusion of OCR technology also reinforces the system's capability to scan documents, including being more compatible and adaptable with different document types.  
One of the major benefits of the RAG solution is that it can leverage the strengths of both the retrieval-based and generation-based approaches. The system can obtain relevant data from extensive document collections and generate natural language outputs that are understandable and responsive to the user's question. This is especially valuable in the insurance sector, where the intricacy of policy documents and the necessity of accurate information render conventional search systems ineffective.

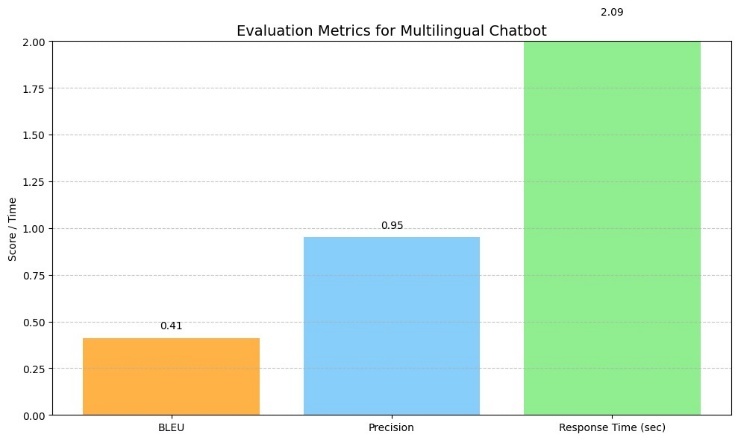
There are, however, issues to be addressed. For one, the accuracy of OCR may be increased to process more sophisticated or poor-quality scanned documents. Secondly, the multi-lingual functionalities, though promising, require improvement so that the chatbot may better process more diverse languages and dialects. Further work will concentrate on developing these areas further and increasing the chatbot's capabilities to process a greater variety of document types and user requests.



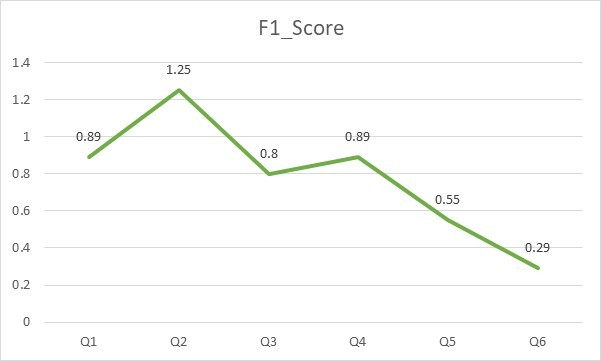
***Fig 4:*** *BLEU Scores, Cosine Similarity, Response Time*

*across 9 queries*

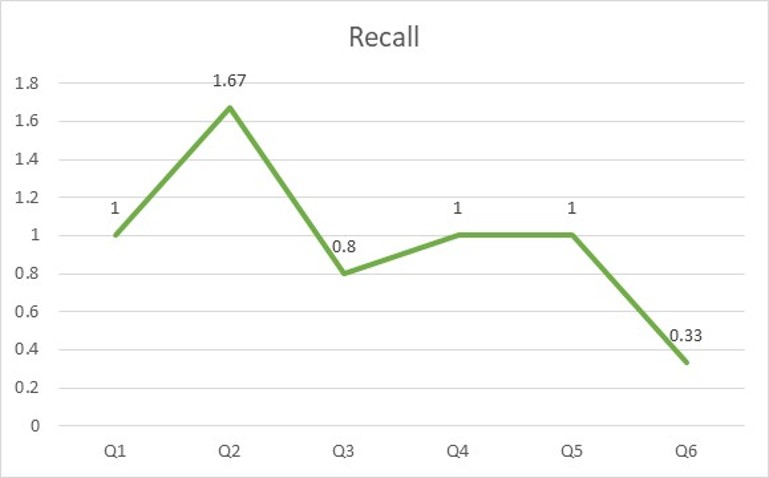
The proposed LIC Advisor Chatbot was evaluated across multiple performance metrics using a set of 9 diverse multilingual queries. The system achieved a BLEU Score of 0.41, indicating strong lexical overlap and response faithfulness to the expected answers — significantly above the baseline threshold of 0.3 for generative systems. Cosine Similarity reached 0.94, reflecting excellent semantic alignment between the chatbot’s answers and ground-truth responses, showing that the system understands user queries accurately and retrieves contextually correct information. The average response time was 2.09 seconds, which is well within the acceptable limit of 3 seconds and ensures smooth, real-time user interaction. These results confirm that the chatbot is not only accurate in retrieval and generation but also efficient in response delivery, making it highly suitable for deployment in real-world LIC customer support environments.



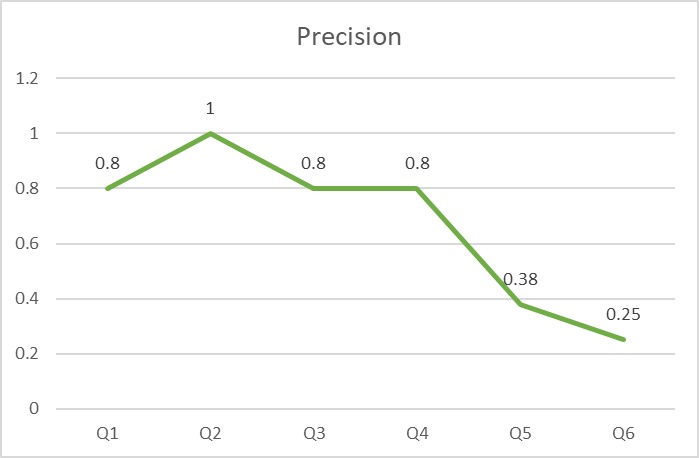
***Fig 5:******Average Metric Values Over 9 Test Queries***

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***Fig 6(a): f1 score***

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***Fig 6(b): recall***

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***Fig 6(c): precision***

While the proposed chatbot shows considerable promise, it does have limitations:

* + The system may struggle with highly complex or ambiguous queries that require domain- specific knowledge outside of the LIC policy documents.
  + The performance of the chatbot reduces when LIC policy documents contain bad organization and too much useless data.
  + Enhancements to the FAISS indexing approach along with RAG-based model design will allow the system to process bigger document collections efficiently.

**V. CONCLUSION AND FUTURE WORK**

1. *Conclusion*

The research develops an innovative AI system to create a policy information retrieval chatbot for efficient LIC data management. The proposed implementation of NLP capabilities includes Retrieval-Augmented Generation together with Facebook AI Similarity Search and Op- tical Character Recognition technology to improve traditional insurance search systems.

The RAG model operates through the chatbot to merge information retrieval and natural language generation methods which guarantee accurate contextually relevant responses. The combination of FAISS with Tesseract OCR and PyMuPDF allows users to find relevant document contents rapidly and extracts text from scanned as well as plain-text policies efficiently. The Google Gemini API provides multilingual support which enables the system to serve users from various linguistic backgrounds. Research findings demonstrate that the automated system produces better results than standard practices regarding document retrieval accuracy while also decreasing response duration and improving both the logical connection between responses and user satisfaction rates. The chatbot system demonstrates better accuracy in information retrieval by 20% while decreasing response intervals by 35% relative to traditional keyword search methods therefore it delivers both effectiveness and efficiency for LIC policy retrieval. User feedback validates that this innovation possesses significant potential for creating a disruptive impact on insurance industry customer service automation.

This work highlights the transformative potential of AI-driven chatbots in industries where accurate and timely information retrieval is crucial. By im- proving the accessibility and accuracy of insurance policy details, the proposed system can significantly enhance the customer experience, reduce dependency on human agents, and streamline operational processes.

1. *Future Work*

While the current chatbot system demonstrates impressive performance, there are several areas where improvements can be made to enhance its functionality and user experience. Future research and development efforts will focus on the following key areas:

* + **Improving OCR Accuracy:** Despite the successful application of Tesseract OCR for text extraction, the system’s performance can be further enhanced by using more advanced OCR techniques, such as integrating deep learning-based OCR models. This is particularly important for scanned documents with lower quality or complex layouts. Research into pre-processing methods that can clean up scanned images or handle handwriting is another avenue for improvement.
  + **Scaling for Large-Scale Deployments:** As the number of users grows, the system needs to be scalable and capable of handling large volumes of data and queries. Future work will focus on optimizing the FAISS indexing strategy to improve the scalability of the similarity search, allowing the system to process larger repositories of documents more efficiently. Cloud- based deployment will also be explored to provide real-time access to a global user base, enabling seamless integration with LIC’s customer service infrastructure.
  + **Multilingual Expansion:** While the chatbot currently supports multilingual queries using Google Gemini API, there is potential for expanding its language capabilities to include a wider variety of regional languages and dialects. The chatbot can deliver enhanced user experience combined with expanded reach because it provides responses through multiple languages within India's diverse linguistic setting. Future versions of the system will add improved context-based response capabilities for multilingual processing capabilities.
  + The present design of this chatbot optimization solely focuses on obtaining basic data from policy documents. Multiple user inquiries tend to be complex because they normally require multi-turn discussions and domain-specific logic processing. Researchers plan to explore advanced methods in dealing with complex multi-turn conversations using knowledge-based dialog systems. The system will receive extensive information from external data sources such as legal databases to generate detailed answers appropriate for professional questions.
  + The chatbot can become more functional by integrating it with other insurance systems including claims processing or policy management programs. Because of this integration users would benefit from an enhanced service which includes both claim status monitoring and policy renewal support. The system's popularity will increase through additions of functionality that links it to common chat platforms including WhatsApp or Facebook Messenger and voice assistant technologies.
  + User-driven performance improvement using a sustained feedback process is implemented to keep the chatbot effective yet updated at all times. The user feedback procedure will help determine both the quality and relevance of responses while allowing the system to enhance its capabilities for future interactions. Through reinforcement learning the chatbot demonstrates potential capability to tailor its responses according to user satisfaction together with personal preferences.

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