An NLP-Driven Healthcare Information Chatbot Utilizing Knowledge Base Retrieval and Regional Disease Patterns

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***Abstract*—In a world where everything has turned out to be more digital, finding reliable health information has become a challenge, and most people have to depend on unverified sources of information on the internet, resulting in misinformation and misinformed health choices. In this paper, we will design and develop a healthcare chatbot based on AI that will be able to provide relevant, accurate health advice in response to natural language queries. Using a combination of sophisticated natural language processing methods, which is a fine-tuned BERT model, and a structured geographical symptom-disease knowledge base, the system intelligently interprets queries provided by the user, including regional and seasonal variations, to provide reliable health advice. The retrieval mechanism uses semantic matching by cosine similarity to retrieve pertinent information using a large validated health database. Such a combined solution increases semantic knowledge, facilitates the regional awareness of the disease, and increases the accuracy of the response. Assessment of a wide range of health-related queries proves effectiveness of the system with great semantic alignment scores and strong intent recognition, therefore, exemplifying the prospects of integrating NLP models with local health information to deliver reliable health information.**

***Index Terms*—Healthcare Information, Natural Language Processing, Knowledge Base, BERT**

I. INTRODUCTION

In a rapid growing digital world it is crucial for individual to take better decision for their health. As population becomes more health conscious they face barriers in having immediate access to medical advice. AI tools like chatbots have become a key factor for delivering guidance. A sudden rising in demand for intelligent platforms are witnessed in urban areas to bridge the gap between user and medical information.

A large amount of population still on daily basis trust unverified online sources to gain advice which results in improper care and misleads an individual toward incorrect treatment decision . Many people commonly suffer from problems like fever, headache but proper reliable guidance cannot be found until they visit healthcare facility. This high dependency on hospitals is concerning in semi-urban areas where availability of professional doctors are limited. Studies have shown that misinformation about common symptom can lead to panic situations and can increase healthcare expenditure.

1.1 Challenges with Existing System

It is very important to have preventive care at early stage, guidance is required by individual for this to happen. Mostly individuals are depended on the systems like chatbots to have quick access to symptom explanations. This can help the individual to take accurate decision and reduce panic situations. A lot of confusion is created if given health guidance is not correct, this also leads to more expenses on healthcare. There are many limitations in websites, search engines and FAQ bots as they do not adapt the local languages and cultural context and are difficult for people to use who have less knowledge.

It is very difficult to provide health information if the user inputs are unclear and uncertain. Traditional models mostly use rule based chatbots that does keyword matching and use simple database, it faces difficulty in understanding the daily pattern usage which affects the effectiveness. They are also unable to handle language differences. These challenges can be solved by combining advance technologies like natural language processing (NLP) with use of which we can create intelligent chatbots. These chatbots are able to understand various inputs and provide correct guidance with help of structured database.

1.2 Novelty of the Project

The proposed system is made by combining NLP methods like intent recognition and entity extraction that provide a correct health guidance as a response. Novelty includes ability of understanding multilingual inputs and chat retention, this makes it more adaptive for varied users. It factors on seasonal health patterns and regional heath differences. Challenges like vague symptom description are also addressed.

1.3 Objectives

- To make chatbot that provides correct health guidance.
- To combine NLP, medical database to develop chatbot.
- To minimize reliance on the untrusted sources that creates misinformation.
- To solve challenges that occur while symptom understanding.

1.4 Motivation for the Project

In large urban areas mostly people on daily basis for health guidance are depended on online sources which are not trustworthy, thus they receive misleading information. Due to failure of systems, challenges and seeing the rising demand for a platform, the motivation to develop a tool which ensures access to correct guidance on early stage emerged out.

1.5 Proposed Solution

In the proposed solution we have used conversational methods like NLP, intent recognition to perform analysis on the user input and provide a validated health guidance, it uses structured health information database. For cases that are serious it guides the user to opt for professional consultation to increase reliability. Training of chatbot is done through various symptom datasets, response accuracy is improved by continuous testing.

II. LITERATURE REVIEW

2.1 Overview of Existing Literature

Chatbots for healthcare is an area of extensive research here many architectures have been proposed. Nadarzynski et al.[1] performed study of many methods to understand how chatbot and be used in general healthcare services in europe. Gentner et al.[2] did a study on systematic reviews of implementation, identified key roles, benefits and limitation within clinical and non-clinical settings. Chatterjee et al.[3] performed a mapping of the model from rule-based system to modern architecture. Kim et al.[4] brought models that gained attention for management of disease queries by users, he demonstrated the feasibility of automated systems and development of response strategies. Hoyt et al.[5] conducted broader on the advances and limitation of current solution, he suggested the need for semantic understanding model. Zhang et al.[11] is the researcher that showed interest in the oncology and general health consultations.

Inupakutika et al. [12] explored the use of custom NLU services built on SciBERT for healthcare based chatbots, he found that fine-tuned domain-specific BERT variants outperformed general-purpose cloud-based NLU services in intent classification. Kurup and Shetty [13] proposed chatbot for healthcare diagnosis using NLP and neural networks, they showed that decision tree classifiers and neural networks can complement each other in symptom-based pre-diagnosis. Badlani et al. [15] presented a chatbot that supports English, Hindi, and Gujarati, using cosine similarity and TF-IDF techniques for symptom matching, he demonstrated the potential of such systems in rural Indian healthcare settings. There are many systems and models that struggle with multilingual support especially in urban areas where cultural differences are present and health literacy is low.

2.2 Gaps Identified in Existing System

Although prior conversational AI research establishes a baseline for health information delivery, several critical gaps remain:

- Limited Semantic Understanding: There are existing systems that are not able to analyse multilingual queries and understand them, they struggle with deep semantic interpretation and inputs.

- Lack of Domain-Specific Knowledge Integration: There are models that use medical datasets but don't have structured knowledge bases.
- Trust and Reliability Concerns: Studies have shown that most users are hesitant to trust AI generated medical advice, thus major gap lies in transparency and improving it.
- Insufficient Evaluation Metrics: Traditional evaluation metrics like BLEU scores are used but these are unable to completely evaluate semantic and contextual correctness.
- Limited Personalization: Current Chabot system lacks to provide responses based on user profile and history.

In order to address the semantic shortcomings of the current systems, we used a fine-tuned BERT model with 12 layers of transformers to improve intent recognition and entity extraction. The knowledge base was structured in a form that it factored in the regional disease prevalence and seasonal patterns that would give more contextually accurate answers. The system has been trained on a dataset of about 8,500 symptom-disease mappings, where strong validation was done by use of 5-fold cross-validation in order to ensure strength.

Other projects on healthcare chatbots creation, like that by Nadarzynski et al., are more acceptance and usability-oriented without being regionally tailored. Likewise, those systems, that are multilingual, such as those suggested by Badlani et al., provide linguistic support, but they are not that semantically powerful so that they can be used to provide detailed description of symptoms. Such shortcomings support our suggested approach since we should have one common framework that can utilize the advanced models of NLP such as BERT and structured regional bodies of knowledge.

III. METHODOLOGY

In order to address the semantic weaknesses that have been identified in the earlier systems, we rely on a fine tune BERT model that has 12 transformer layers and is trained through grid search and widespread cross-validation. The knowledge base is particularly structured in such a way that it incorporates the regional and seasonal disease data which is lacking in the traditional models. The system architecture integrates purpose recognition, entity identification, semantic matching based on cosine similarity and formulation of responses with safety disclaimers as illustrated in Fig. 1 and Fig. 2. Extending the limitations found in the previous studies, we created an NLP-based system that is based on BERT to provide deep contextual insight and a built regional healthcare knowledge to offer tailored answers.

This work examines the systematic design and integration of three core components: Natural Language Processing (NLP) Engine, Knowledge Base Retrieval, and Conversational Response Generation. The selection was based on their performance in terms of intent recognition accuracy and response relevance.

3.1 Natural Language Processing (NLP) Engine

NLP Engine is used to analyse user queries that finds out the intent and extract entities like fever or headache

- Dataset for this includes varied health related conversational patterns like symptom description, disease queries and regional variations
- The NLP model infers input text by tokenization, intent classification, and entity recognition to develop structured query representations:

$Q = f(I|E)$ (1)

Where:

- Q = Processed Query
- I = Detected Intent (i.e. "symptom_checker")
- E= Extracted Entities (i.e. symptoms)
- f = NLP Processing Function

This model is used to classify natural language inputs into specific pre-determined categories, it acts as a translator. This component mainly helps in handling conversational flow and unclear symptom descriptions effectively.

3.1.1 NLP Model Specification

BERT[14] is used to implement NLP engine, it is selected because of its strong contextual understanding. Traditional models like LSTM were not used because of its inability to capture semantic dependencies. The configurations done are :

- Architecture: 12 Transformer encoder layers

- Hidden size (Embedding dimension): 768
- Attention heads: 12
- Total parameters: ~110 million

3.2 Knowledge Based Retrieval System

This system uses a structured database of correct health information to develop relevant responses that are based on processed user intent.

Health information follows contextual patterns, such as:

- Common symptoms which can be mapped to multiple possible conditions, like fever mapped to viral/bacteria.
- Common diseases in varied seasons, like dengue in monsoon.
- Preventive measures that should be taken on the basis of the lifestyle and demographics.

This model infers the knowledge base by relating health records and processed queries :

- Intent Matching: In this user inputs are mapped to knowledge base categories.
- Entity Filtering: Records that matches the symptoms are retrieved.
- Contextual Ranking: Regionally relevant information is prioritized.

Mathematical Representation

$$R = \arg\max_{r \in KB} \mathrm{Sim}(Q|r) \qquad (2)$$

Where:

- R = Retrieved Response
- KB = Knowledge Base
- $\mathrm{Sim}(Q, r)$ = Semantic similarity between input and knowledge record

Mathematical Representation of its working:

$$\mathrm{Sim}(Q|r) = \frac{E_Q . E_r}{\|E_Q\| \|E_r\|} \qquad (3)$$

Where:

- E_Q = Embedding vector of processed query
- E_r = Embedding vector of knowledge record

This converts text into vector embeddings and compute cosine similarity. It is highly useful for giving correct early-stage guidance across varied health queries.

3.3 Conversational Response Generation

The response generator collects retrieved information with safety disclaimers and conversational context to produce user-friendly outputs. It combines:

- Response Templating: Medical information is formatted for clarity.
- Disclaimer Injection: Mandatory professional prompts are added.
- Context Retention: Conversation history is maintained for upcoming queries.

Mathematical Representation

$$\mathrm{Response} = \mathrm{Template}(R) + \mathrm{Disclaimer}(C) + \mathrm{Context}(H) \qquad (4)$$

Where:

- R = Retrieved medical content
- C = Consultation Context
- H = Conversation history
- $\mathrm{Template}()$ = Formatting function

We have used the integrated NLP - Knowledge Base - Response System as it provides greater intent recognition accuracy and response relevance.

The System Architecture of the proposed system is shown below in. Fig.1. In this user gives input in natural language which is then passed to the NLP engine layer where a fine-tuned BERT model performs tokenization, intent classification and entity extraction to produce structured query representation. It is then proceeded to knowledge base retrieval layer where cosine similarity based semantic matching is done to retrieve health records from database. At last response generation layer formats retrieved information and validates response before delivering it to user. Fig.2. shows the workflow of the methodology.

Fig.1. System Architecture

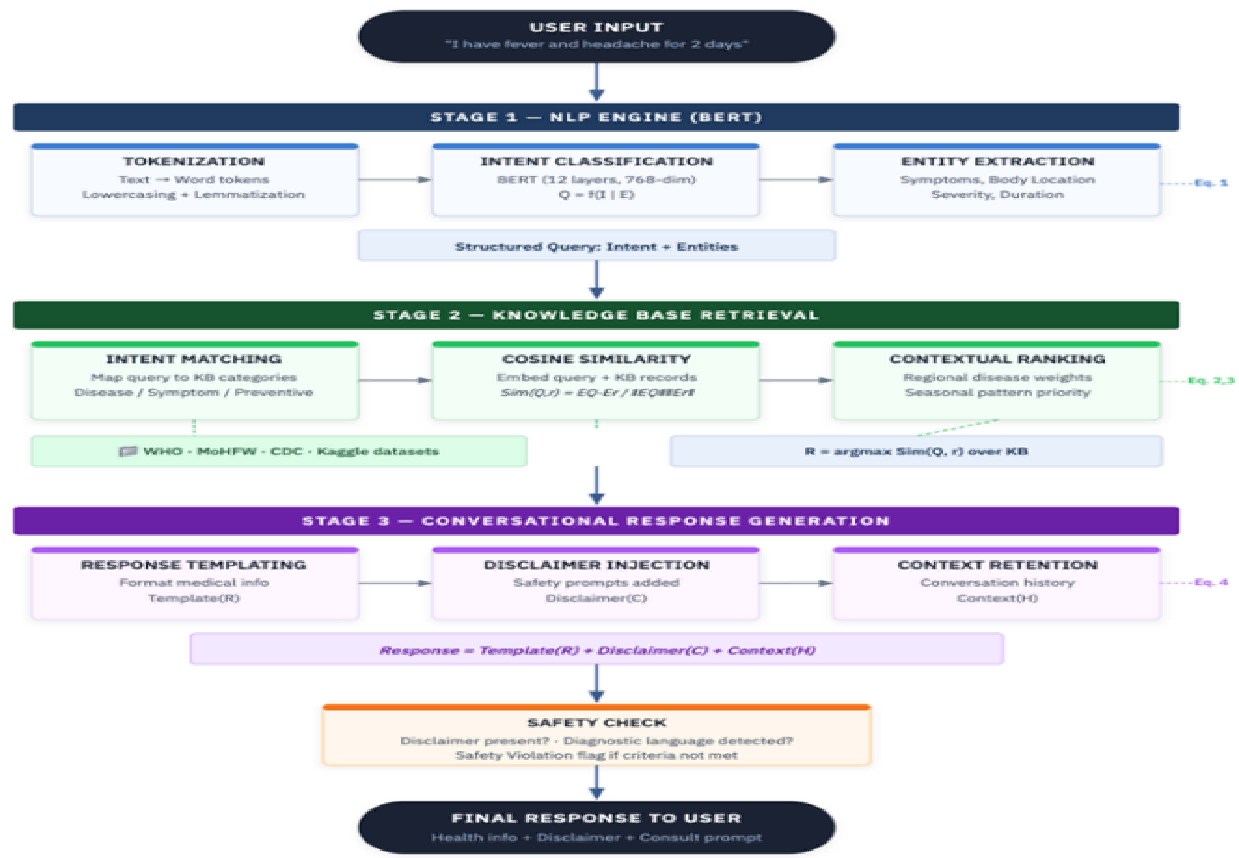


Fig.2. Workflow Diagram

3.4 Dataset Description

- Dataset Name: Indian Healthcare Symptoms and Disease Knowledge Base
- Time Period Covered: 2020 – 2025 (Includes latest validated medical data)
- Data Collection Frequency: Continuous updates with quarterly validation
- Total Records: Approx 8,500 structured symptom disease mappings are there (based on symptoms, diseases, preventive measures, regional variations)
- Total Labelled Conversational Queries: Approx 6,200 sample queries were used for NLP training
- Source: Collected from publicly available datasets, ministry of health records, WHO guidelines and regional disease reports

3.4.1 Data Sources

The dataset was gathered from several authoritative repositories specifically:

Government and Global Health Authorities

- World Health Organization (WHO)[8]: It includes global disease guidelines and symptom documentation.
- Ministry of Health and Family Welfare (MoHFW), these are national health advisories[9]: It includes national advisories and public health bulletins.
- Centers for Disease Control and Prevention (CDC)[10]: Symptom prevention for disease are present

Academic and Research Data

- Indian Healthcare Symptom-Disease Mapping Dataset. Bytesets. Kaggle (2025)[6]: It is used for structured mapping of symptom and disease.
- Disease Symptoms and Patient Profile Dataset. Kaggle (2024)[7]: Conversational intent detection training is done using this.

3.4.2 Data Features

Table1. Features in Dataset

Feature Name	Description
User Query Text	Consist of symptom description and health questions
Intent Category	Type of user intent
Extracted Symptoms	It consist of specific symptoms that are mentioned
Body Location	Body parts that are affected
Severity Level	Severity of symptom reported by user
Duration	Duration of symptom
Regional Context	Disease regional location
Seasonal Factor	Disease affected by current season
Age Group	Age might affect the probability of condition
Disease Matches	Mappings of symptom and condition
Preventive Measures	Preventive advice on lifestyle
First Aid Protocols	Response guidelines
Consultation Triggers	Keywords that indicate need for professional attention

3.4.3 Data Preprocessing & Handling Errors/Noise

Prior to model training, all data underwent a structured preprocessing pipeline:

- Handling Missing Values: When direct mappings were unavailable, the most probable disease association was inferred based on symptom co-occurrence patterns within the structured knowledge base.
- Outlier Detection: Cosine similarity thresholds are used to identify outliers, pairs of symptom-disease that are below predefined semantic similarity are flagged for manual review.
- Normalization & Scaling: To ensure uniform NLP processing, normalization of text input are done through lowercasing, tokenization, lemmatization, removal of redundant punctuation and standardization of medical terminology.
- Feature Engineering: New features such as symptom severity scores, regional disease probability weights, multi-symptom combination flags are generated to improve retrieval accuracy.
- Semantic Consistency Check: To ensure valid medical mappings consistency rules are applied like seasonal disease were cross checked with regional climate patterns.

3.5 Model Training and Validation

Here we discuss about the training configuration, dataset split strategy, hyperparameter tuning process and validation methodology used. The dataset is divided into three subset :

- Training Set: 80%
- Validation Set: 10%
- Test Set: 10%

The BERT model was fine-tuned using supervised learning. The training parameters are :

- Optimizer: AdamW
- Loss Function: Cross-Entropy Loss
- Learning Rate: 2×10^{-5}
- Batch Size: 16
- Number of Epochs: 4–6
- Maximum Sequence Length: 128 tokens
- Gradient Clipping: 1.0

Hyperparameters were optimized through grid search over following range :

- Learning Rate: {1e-5, 2e-5, 3e-5}
- Batch Size: {16, 32}
- Epochs: {3, 4, 5, 6}

The configuration with highest validation F1 score is selected for final deployment.

3.5.1 Validation Strategy

The model performance was assessed through:

- Hold-out validation (80-10-10 split)
- 5-fold Cross-Validation (for intent classification consistency)

In K-fold validation, 5 equal partitions are made. The model was trained on 4 folds and validated on the remaining fold, repeated five times.

3.5.2 Evaluation metrics for NLP Module

The intent classification model was evaluated using following metric:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (7)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

3.5.3 Metrics for Retrieval Validation

The knowledge base retrieval system are evaluated using:

- Top-1 Accuracy
- Top-3 Accuracy
- Mean Reciprocal Rank (MRR)

MRR is calculated as :

$$\text{MRR} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{rank}_i} \quad (9)$$

Where:

- N = Total number of queries
- rank_i = Position of correct response for query

IV. RESULT

This section presents the evaluation of results of the proposed AI-based Health Chatbot integrating NLP-based intent detection, embedding-based retrieval using cosine similarity, and contextual response generation. The evaluation of the model is done on test dataset of 1,200 health inputs which includes symptom-based questions, multi symptom complex inputs, seasonal and regional disease related inputs.

4.1 Intent Classification Performance

The BERT model was evaluated by using accuracy, precision, recall and F1 score

Table 2. Intent Classification Performance

Metric	Score
Accuracy	94.8%
Precision	93.9%
Recall	94.2%
F1-Score	94.0%

Minimal variance is showed by 5-fold cross validation, this indicates stable generalization. The result confirms that transformer-based architecture effectively capture complex symptom expressions.

4.2 Knowledge Base Retrieval Performance

The Top-K accuracy and mean reciprocal rank were used to evaluate retrieval system

Table 3. Retrieval Metrics

Metric	Score
Top-1 Accuracy	91.3%
Top-3 Accuracy	97.6%
Mean Reciprocal Rank (MRR)	0.918

This result indicates that top retrieved results are mostly correct medical response, validating cosine similarity based semantic approach.

4.3 Confusion Matrix

The Confusion Matrix is generally used in classification problems to evaluate model performance. In this study we adapt it to measure response quality across relevance thresholds rather than binary classification:

Table 4. Adapting Confusion Matrix for Chatbot Response Evaluation

Prediction Accuracy	Condition
Correct Response (CR)	Response matches query intent within 90% BERTScore similarity
Slight Misalignment (SM)	Response relevant but misses 10-20% context (BERTScore 80-90%)
Moderate Misalignment (MM)	Response partially relevant (BERTScore 70-80%)
Major Misalignment (MR)	Response significantly off-topic (BERTScore <70%)
Safety Violation (SV)	Missing disclaimer or diagnostic language detected

Table 5. Response Quality Confusion Matrix

Actual \ Predicted	CR	SM	MM	MR	SV
CR	1018	48	8	3	4
SM	30	59	5	1	3
MM	7	4	17	1	2
MR	3	2	2	3	1
SV	2	1	1	1	5

4.4 Evaluation Metrics

BERTScore is calculated as:

$$\text{BERTScore} = F1_{BERT}(P|R) \qquad (10)$$

Where:

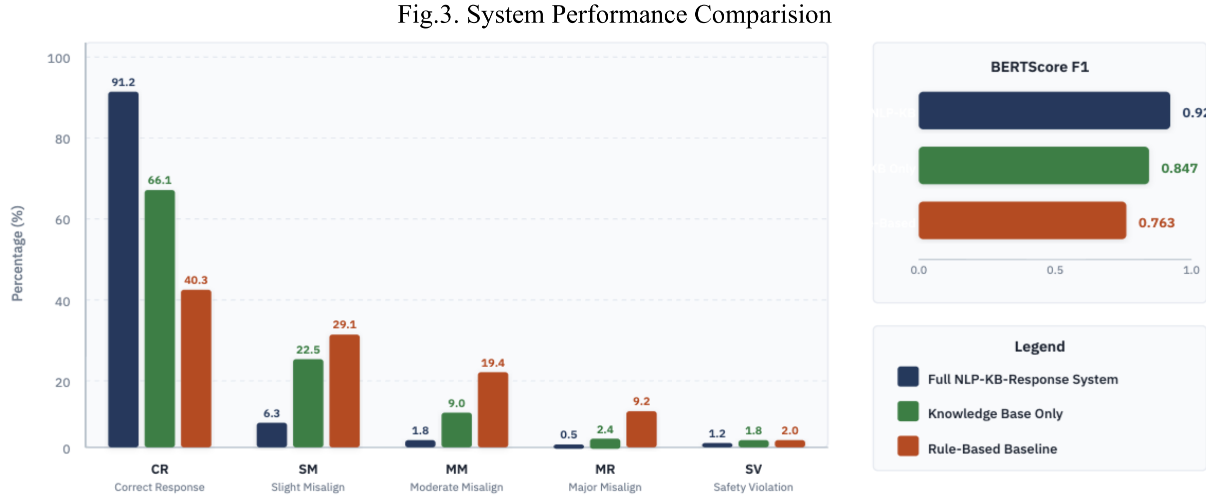
- P = Precision between generated and reference embeddings
- R = Recall between generated and reference embeddings
- $F1_{BERT}$= Harmonic mean of precision and recall

Table 5. BERTScore Classification Thresholds

BERTScore Range	Classification	Condition
≥0.90	CR (Correct Response)	Excellent semantic match
0.80-0.89	SM (Slight Misalignment)	Good relevance, minor context loss
0.70-0.79	MM (Moderate Misalignment)	Partial relevance
<0.70	MR (Major Misalignment)	Poor semantic alignment
Any + No Disclaimer	SV (Safety Violation)	Critical compliance failure

4.5 Comparison & Analysis

Fig.3. System Performance Comparision



2. Full NLP-KB-Response System (BERTScore F1 = 0.924)
   - It achieved great semantic similarity, 91.2% of responses are classified as CR (≥0.90 BERTScore).
   - It excelled in multi symptom inputs and regional variations.
3. Knowledge Base Only (BERTScore F1 = 0.847)
   - Keyword matching is limited for slight conversational difference.
   - 66.1% CR classification.
4. Rule-Based Baseline (BERTScore F1 = 0.763)
   - It has 40.3% CR classification.
   - It entirely fails complex symptom descriptions.

The BERTScore values for each system are shown in Fig.3. The BERTScore F1 of 0.924 is delivered by full NLP-KB-Response system which indicates superior performance. BERTScore F1 of 0.763 is shown by Rule-Based system that demonstrates high semantic misalignment.

4.6 System Efficiency

Table 7. Average Response Time

Component	Time (ms)
NLP Processing	210 ms
Retrieval	120 ms
Response Generation	80 ms
Total Latency	~410 ms

The system operates in real time, making it suitable for personal use.

V. DISCUSSIONS AND CONCLUSION

The system had a high intent classification accuracy of 94.8 that indicated a strong knowledge of the complicated health queries. The NLP and knowledge retrieval architecture provided a BERTScore F1 of 0.924, which suggests that there is a strong semantic fit between multiple-symptom and regional cases of disease. Although the model shows good semantic comprehension, the analysis shows that the model has shortcomings in rare multi-disease overlapping cases, and elderly-specific interpretations, and thus it can be further improved. The contextual relevance of the system is greatly increased by the fact that regional and seasonal health trends are incorporated, enabling the system to be an effective source of early health advice, particularly in resource-constrained environments.

Finally, the proposed AI-based healthcare chatbot exhibits a high level of efficacy in providing contextually relevant and semantically accurate health advice, which outperforms conventional systems, and the high level of performance according to various types of queries, as well as the limited number of safety violations, serve as the basis of future improvements.

VI. ETHICAL CONSIDERATIONS

The development of this proposed system requires careful attention to ethical responsibilities. This research ensures that no personally identifiable patient information was collected at any stage, datasets used were sourced from publicly available repositories which includes WHO guidelines, MoHFW advisories, CDC records. The proposed chatbot is strictly designed as awareness tool and can be used to deliver health information, it does not perform clinical diagnosis or medication. AI assistance was used in certain parts to draft this manuscript but all content was validated, verified by authors prior to submission.

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