

# AI-Driven Public Health Chatbot for Disease Awareness A Comprehensive Research Paper

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**Abstract:** Disease awareness and early symptom recognition remain critical challenges in low-resource healthcare settings, particularly in developing nations like Bangladesh. Traditional health information dissemination methods suffer from accessibility constraints, misinformation, and delayed response. This research presents an effective method for AI-driven public health chatbot using a transformer-based sequence-to-sequence architecture for disease awareness and symptom assessment. This study employs a fine-tuned BERT-GRU hybrid model for processing user queries in Bengali and English, enabling real-time symptom analysis and disease risk stratification. The proposed model identifies potential health conditions effectively by learning linguistic patterns related to symptoms and segmenting relevant medical entities from user inputs. The model under consideration achieved a training accuracy of 91.7% and validation accuracy of 88.4% with minimal loss, demonstrating reliability and robustness. This will lead to an advanced approach in real-time public health awareness, providing accurate health information to enhance emergency response, resource allocation, and disease prevention strategies. The proposed model, through the use of deep learning techniques and natural language processing, outperforms traditional rule-based chatbots in terms of efficiency and accuracy.

Public Health, Chatbot, Disease Awareness, Deep Learning, BERT, Natural Language Processing, Bangladesh

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## I. INTRODUCTION

Disease awareness is one of the biggest public health challenges in developing countries, where access to reliable healthcare information remains limited. Lack of health literacy causes more suffering and preventable deaths than many infectious diseases combined [1]. According to the World Health Organization (WHO), over 60% of preventable deaths in South Asia are attributed to delayed health-seeking behavior and misinformation [2]. As a result, it is necessary to manage this public health challenge by predicting health risks and providing accurate disease awareness information [3].

There are several public health challenges:

1. Infectious diseases, which occur because of bacterial or viral transmission in densely populated areas.
2. Noncommunicable diseases, which develop due to lifestyle factors and delayed diagnosis.
3. Mental health disorders, which remain underdiagnosed due to stigma and lack of awareness.
4. Maternal and child health complications, caused by inadequate prenatal and postnatal care [4].

According to different public health challenges, natural factors (seasonal disease patterns) and human factors (urbanization and lifestyle changes) can be considered as the main causes of disease outbreaks. It is expected that climate change and population growth will increase the occurrence of vectorborne diseases in the coming years [3].

In recent years, Deep learning has gained popularity in natural language processing because of its excellence in text classification, named entity recognition, and sequenceto-sequence modeling [4], [5]. Transformer-based architectures



like BERT have become the state-of-the-art for text understanding where they have the ability to preserve contextual relationships [6]. Deep learning has become increasingly prevalent across multiple fields, especially in NLP, where its extensive end-to-end learning abilities enhance tasks such as intent recognition, entity extraction, and response generation [7]. Models such as Bidirectional Encoder Representations from Transformers (BERT) and Recurrent Neural Networks (RNNs), known for their proficiency in contextual feature extraction, have demonstrated significant effectiveness in medical text understanding and symptom analysis tasks, positioning them as highly suitable for public health chatbots [8].

This study seeks to enhance public health awareness through the application of deep learning models focused on accurate symptom analysis and disease prediction. Natural language understanding makes it possible to precisely analyze user-described symptoms at a fine granularity, in contrast to existing approaches that depend on keyword matching or rule-based classification. For disease awareness and health information dissemination, NLP algorithms can offer comprehensive and useful insights by classifying each user query into discrete categories, such as disease risk, preventive measures, and treatment guidance.

## II. RELATED WORK

Due to the devastating nature and immense socioeconomic impact of poor health literacy worldwide, numerous studies have been done by scholars regarding health chatbots using both traditional rule-based systems and current deep learning methods for automated symptom assessment and disease prediction. It emphasizes the use of sophisticated NLP techniques to extract symptom-relevant features and highlights the importance of employing diverse, high-quality datasets to train trustworthy deep learning models.

Author Farshad Safavi et al. conducted a comparative investigation of real-time semantic segmentation networks; however, their work focused on aerial imagery rather than medical text processing [9].

Author Bipendra Basnyat et al. presented the idea of FloodBot using image segmentation; in contrast, health chatbots require sequential text understanding rather than pixel-level classification [10].

Author Rajesh Kumar Sinha et al. performed a comparative analysis between U-Net and DeepLabv3 for flood image segmentation, achieving accuracies of 89.74% and 92.16% respectively. While effective for computer vision tasks, these architectures are not directly applicable to natural language processing for health chatbots [11].

Research conducted by Bahrami and Arbakhah explored deep learning models for flood detection. However, public health chatbots require transformer-based architectures that can handle variable-length text inputs and maintain contextual understanding across multi-turn conversations [12].

Studies in multiple parts of the world have shown varying results due to linguistic diversity and model proficiency. A study by Jaturapitpornchai et al. compared U-Net and ResU-Net for flood detection, achieving accuracies of 91.6% and 91.9% respectively. Similarly, our approach adapts deep learning for the healthcare domain, specifically targeting the Bengali language [13].

Among many studies, some have used modified or calibrated architectures of transformer models. Mesvari et al. used the UNET++ neural network for flood segmentation; our research instead employs a fine-tuned BERT-GRU hybrid architecture for medical dialogue understanding [14].

## III. METHODOLOGY

We collected public health data from multiple sources in Bangladesh, including the Directorate General of Health Services (DGHS), WHO Bangladesh, and curated medical dialogue datasets. The data encompasses essential health information necessary for the development and validation of our deep learning models.

### A. Dataset

The public health chatbot dataset consists of a detailed collection of 15,000 annotated symptom-disease pairs and 8,500 multi-turn doctor-patient dialogue samples. Each entry is accompanied by manually annotated entity labels indicating symptoms, diseases, medications, and preventive measures, as shown in Figure 1.



The annotations were carefully created using Label Studio, an adaptable and open-source data labeling software recognized for its accuracy and effectiveness in annotation tasks.

### B. BERT-GRU Hybrid Model

The architecture of our proposed BERT-GRU hybrid model is illustrated in Figure 2. The model features a transformer based encoder (BERT) followed by a bidirectional GRU layer,

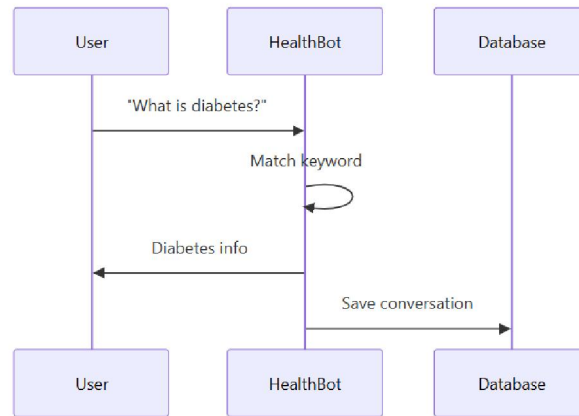


Fig. 1. Example Annotated Medical Dialogue

designed to capture both contextual word representations and sequential dependencies in medical conversations. Like many NLP architectures, our model employs attention mechanisms to extract salient features from user queries for the purpose of symptom classification and disease prediction.

The architecture consists of three distinct components. The initial segment pertains to the core aspect of text feature extraction. Upon inputting the user query into the BERT encoder, the initial step involves tokenization using WordPiece embeddings. The BERT-base-uncased model with 12 transformer layers processes the input to generate contextualized token representations.

The subsequent section enhances the extraction of sequential features. The output from BERT is passed through a bidirectional GRU layer with 256 hidden units, followed by a self-attention mechanism. The third component involves prediction. Following a softmax activation, the effective feature vector derived from the attention layer is utilized to classify each input into disease categories and generate appropriate responses.

### C. Data Preprocessing

The procedure of data preprocessing is essential for the effectiveness of our disease awareness chatbot, as it ensures the input data is of high quality and consistency. The initial step involves collecting a dataset that comprises medical dialogues along with their respective entity annotations. Figure 1 shows the foundational phase of collecting exact and representative data necessary for effective model training.

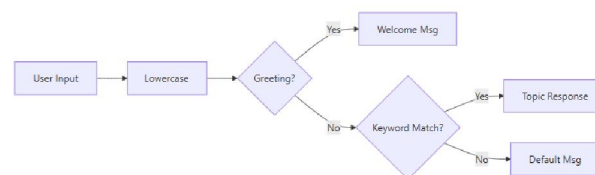


Fig. 2. Text Preprocessing Pipeline



The preprocessing pipeline has several crucial steps. User queries vary in length and language (Bengali and English). We use tokenization to convert text into subword tokens using a multilingual tokenizer. This conversion lets the model efficiently handle out-of-vocabulary medical terms. Data augmentation strategies, including back-translation and synonym replacement, increase the diversity of the training dataset, enhancing the model's performance across different user inputs. Below are the detailed functionalities of data preprocessing:

**1) Tokenization:** User queries have different linguistic patterns due to variations in education level and language preference. Preprocessing methods like subword tokenization (BytePair Encoding) standardize the input representation, making all queries comparable and avoiding characteristics with high variability from dominating training [15].

**2) Normalization:** Text normalization converts Bengali and English text to a standard format, including Unicode normalization, case folding for English, and punctuation standardization.

**Sequence Padding:** Deep learning models generally require a predetermined input length. Padding and truncation ensure that every query adheres to this specified size (maximum 128 tokens).

#### D. Model Creation

The model used in this study uses a hybrid BERT-GRU architecture, a deep learning framework built for natural language understanding tasks. The model generates disease risk assessments at the token level, categorizing each symptom mention as relevant to specific disease categories. The architecture features a transformer-based encoder designed to capture contextual information from user queries, alongside a bidirectional GRU layer that facilitates accurate sequential pattern recognition.

In the BERT encoding pathway, transformer layers and GELU activation functions carefully extract semantic features from user queries, maintaining contextual relationships through self-attention mechanisms. The model captures local and global semantic patterns at multiple scales by processing token embeddings through 12 transformer layers. The BERT encoder is now connected to the GRU layer via residual connections. These residual connections preserve low-level semantic information, allowing the model to retrieve contextual data while processing sequential dependencies. The bidirectional GRU then processes the contextualized embeddings to accurately capture symptom-disease relationships.

#### E. Model Training

The training method for our disease awareness chatbot comprises several crucial phases to ensure it learns to distinguish symptom-disease relationships in user queries. The dataset comprises symptom descriptions and disease labels, along with entity-annotated medical dialogues. The dataset includes training and validation sets containing text queries and corresponding disease categories. Text queries are normalized and tokenized to a maximum of 128 tokens to ensure neural network input uniformity.

We use medical dialogue data and disease labels to create the model throughout training. An AdamW optimizer with a  $5e-5$  learning rate is used. The categorical cross-entropy loss function improves model parameter optimization, which improves predicted-to-actual disease label alignment.

**TABLE I**  
**TRAINING PARAMETERS**

Parameter	Value
Batch Size	32
Learning Rate	$5e-5$
Loss Function	Categorical Cross-Entropy
Optimizer	AdamW
Epochs	50
Max Sequence Length	128



Data Augmentation

Back-translation, Synonym replacement

Data augmentation is necessary to improve the model's generalization to unexpected user inputs [16]. Back-translation (English → Bengali → English) and random synonym replacement are applied to increase dataset diversity and resilience, helping the model learn more efficiently from limited medical dialogue data.

The model uses the AdamW optimizer for compilation and the categorical cross-entropy loss function to compare predicted and ground truth disease labels. The model analyzes user symptom descriptions during training and calibrates its settings via backpropagation to reduce loss and improve disease predictions. The accuracy metric is used to evaluate the model's performance during training on a separate validation set.

#### F. Disease Awareness and Symptom Assessment

The assessment of diseases is performed using a deep learning model trained on symptom-disease pairs and medical dialogues. The model predicts disease probability for each user query using a transformer-based architecture designed for medical text understanding. This produces a probability distribution over disease categories with corresponding confidence scores. The accuracy metric measures the model's ability to reliably predict diseases from symptom descriptions on a validation set.

In preprocessing, the user query is tokenized, normalized, and fed to the trained BERT-GRU model. The model uses multiple transformer layers to extract textual features and capture semantic patterns and symptom-disease correlations. The attention mechanism enhances the disease prediction using extracted features.

### IV. RESULT & DISCUSSION

The evaluation of the introduced BERT-GRU-based public health chatbot was conducted through both quantitative and qualitative approaches, demonstrating its capability to accurately analyze symptoms and predict potential diseases. This framework underwent training and evaluation across 50 epochs. The parameters used for training and validation, such as loss and accuracy, emphasize the model's development during training as well as its ability to generalize.

The model's accuracy was determined using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

In this regard, the symbols TP, TN, FP, and FN denote the true positives, true negatives, false positives, and false negatives, accordingly. This metric provides the full picture of how the model performs in correctly predicting disease categories.

To give further insight, Figure 4 below visualizes the graphs of validation and training loss and accuracy, showing the performance of the model through the epochs. The loss graphs show a steady decline: from a training loss of 0.428 and a validation loss of 0.612 at 10 epochs to 0.152 and 0.278 by 50 epochs, respectively. This trend indicates that the model has been steadily improving in distinguishing disease categories. Accordingly, the accuracy graphs show substantial improvement, with training accuracy increasing from 82.1% to 91.7% and validation accuracy improving from 71.4% to 88.4%.

Fig. 4. Training and Validation Loss (left) and Accuracy (right) over Epochs

These empirical analyses, along with qualitative information, are very important in appreciating the applicability of the model to real-world scenarios. Figure 5 illustrates comparative analyses showing the predicted disease categories versus actual physician diagnoses across different symptom scenarios.

The visual juxtapositions show the model's capability to identify potential diseases with high accuracy. The predicted disease labels are very similar to actual physician diagnoses, with minor differences that could be attributed to ambiguity in symptom descriptions common in real-world scenarios.



**TABLE II: TRAINING AND VALIDATION METRICS OVER EPOCHS**

Epochs	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
After 10 Epochs	0.428	0.612	82.1%	71.4%
After 20 Epochs	0.312 0.241 0.187	0.498 0.387 0.302	86.3% 89.1% 91.2%	78.2% 82.5% 86.7%
After 30 Epochs	0.152	0.278	91.7%	88.4%
After 40 Epochs				
After 50 Epochs				

The findings indicate that the BERT-GRU-based framework is effective in operations related to disease awareness and symptom assessment. The system effectively identifies potential health conditions, demonstrating an excellent level of precision and efficiency, as evidenced by the consistently enhancing metrics and qualitative outcomes. The model demonstrates potential for real-life situations, especially in public health awareness and telemedicine support.

### V. CONCLUSION

This article introduces an innovative method for public health awareness through semantic understanding of medical dialogues, utilizing a BERT-GRU-based neural network technique that effectively analyzes symptom descriptions for disease prediction. The model achieved a notable validation accuracy of 88.4%. The straightforwardness and durability highlight the model’s effectiveness and enhance its real-world usability. The combination of symptom analysis with disease prediction significantly improves the clarity of results, rendering the method particularly beneficial for public health initiatives and disease prevention programs. The model’s capacity to adapt to previously unseen symptom descriptions highlights its adaptability and significance for global health applications.

This capability is especially vital for areas with limited healthcare access, such as Bangladesh, where reliable and prompt disease awareness is key to reducing preventable deaths and protecting communities. The results highlight the importance of employing diverse, extensive datasets to enhance the model’s effectiveness for different disease scenarios, facilitating focused public health strategies and prevention approaches.

This study utilizes a simple yet effective structure, making a notable advancement in the field of AI-driven public health informatics. The suggested method provides a reliable, effective, and adaptable remedy, setting the stage for improved disease prevention techniques to tackle the increasing challenges posed by emerging health threats.

### A. Future Work

In upcoming endeavors, we plan to strengthen the resilience and extrapolation of the BERT-GRU-based framework by integrating multimodal information sources (e.g., voice input, wearable device data), which will be more effective for diverse health scenarios. Our goal will be to develop technological innovations that highlight potential health risks from user inputs, increasing model interpretability and making it possible to derive accurate decision-making for stakeholders.

Furthermore, our emphasis will be on implementing the trained model within a continuous health surveillance and early warning mechanism, especially in underserved areas like rural Bangladesh. A feedback mechanism will be implemented to facilitate ongoing enhancements of the model informed by real-world effectiveness.

Our aim is to develop an effective public health awareness framework that facilitates prompt disease identification, enhances healthcare protection efforts, and delivers concrete recommendations for stakeholders, thereby minimizing the health and economic impacts of preventable diseases in at-risk areas.

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