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An Intelligent AI-Driven Primary Healthcare Triage Chatbot with Explainable Risk Classification

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Abstract- The increasing demand for accessible and efficient primary healthcare services highlights the need for intelligent systems capable of early-stage patient triage. Traditional healthcare systems often face challenges such as overcrowding, delayed diagnosis, and limited accessibility, particularly in resource-constrained environments. Existing studies have applied artificial intelligence and machine learning techniques, including Random Forest, Support Vector Machines, and deep learning models, for disease prediction and clinical decision support, along with basic chatbot systems for symptom collection. However, these approaches lack explainability, real-time interaction, and structured risk classification, reducing their reliability and user trust. To address these limitations, this research proposes an intelligent AI-driven primary healthcare triage chatbot that integrates explainable AI with risk-based classification. The system analyses patient symptoms to categorize cases into low, medium, and high-risk levels while providing transparent reasoning, thereby improving accessibility, enhancing trust, and supporting efficient decision-making in primary healthcare systems.

Keywords— Artificial Intelligence, Healthcare Triage, Explainable AI (XAI), Chatbot Systems, Risk Classification, Machine Learning, Clinical Decision Support

I. INTRODUCTION

A. Background of the Study

The field of primary healthcare is undergoing rapid transformation with the integration of Artificial Intelligence and intelligent digital systems. In recent years, AI-driven approaches have been widely adopted for disease prediction, patient monitoring, and clinical decision support, significantly improving healthcare efficiency and accuracy [2], [5], [10]. One of the emerging applications in this domain is healthcare triage, which involves prioritizing patients based on the severity of their symptoms to ensure timely and appropriate medical intervention. With the growing global population and increasing pressure on healthcare infrastructure, efficient and scalable triage mechanisms have become essential to optimize patient flow and enhance service delivery [1], [11].

The importance of this problem is particularly evident in primary healthcare settings, where early diagnosis and timely intervention can significantly influence patient outcomes.

Traditional triage methods rely heavily on manual assessment, which can be time-consuming, inconsistent, and prone to human error, especially in resource-limited regions.

Recent advancements in AI-based systems, including machine learning models and chatbot technologies, have enabled automated symptom analysis and preliminary diagnosis [3], [6], [7]. Furthermore, the integration of Explainable AI has been recognized as a critical requirement to enhance transparency and user trust in healthcare applications [8]. By providing interpretable risk classification and real-time interaction, AI-powered triage chatbots have the potential to significantly improve accessibility, efficiency, and reliability in primary healthcare services.

B. Problem Statement

The increasing demand for efficient and accessible primary healthcare services has created a critical need for intelligent systems capable of performing accurate and timely patient triage. In many healthcare settings, particularly in resource-constrained environments, patients experience delays due to overcrowded facilities, limited healthcare professionals, and inefficient manual triage processes. These challenges often result in delayed diagnosis, improper prioritization of cases, and increased risk of complications.

Existing approaches based on Machine Learning and Artificial Intelligence have demonstrated promising results in disease prediction and clinical decision support. However, these systems are often limited by their lack of real-time interaction, minimal integration with conversational interfaces, and dependence on static datasets.

A major limitation of current systems is their black-box nature, where predictions are generated without clear explanations, thereby reducing trust among users and healthcare professionals. Furthermore, most existing solutions fail to incorporate structured risk classification (such as low, medium, and high), which is essential for effective triage decision-making. Consequently, there is a clear need for an intelligent, explainable, and interactive healthcare triage system that can accurately assess patient symptoms, provide transparent reasoning, and deliver real- time risk-based classification.

C. Motivation

The growing integration of Artificial Intelligence in healthcare, combined with increasing global health challenges, makes this research highly relevant in the current era. Rapid urbanization, population growth, and the rising prevalence of chronic and infectious diseases have placed significant pressure on healthcare systems worldwide. Events such as the COVID-19 pandemic have further exposed the limitations of traditional healthcare infrastructures, particularly in managing large patient volumes and ensuring timely medical assistance [15]. Consequently, there is an urgent need for scalable and intelligent solutions that can support early-stage healthcare delivery and improve system efficiency.

One of the key motivations behind this work is to enhance accessibility to primary healthcare services, especially in rural and underserved regions where medical resources are limited. Many individuals delay seeking medical care due to long waiting times, lack of awareness, or unavailability of professionals. AI-driven systems, including chatbot-based healthcare assistants, have shown potential in providing real-time interaction and preliminary diagnosis.

Furthermore, the integration of Explainable AI addresses critical challenges related to transparency and trust in AI- based systems. By offering clear reasoning for risk classification, the proposed system enhances user confidence and supports informed decision-making. Overall, this approach has the potential to reduce the burden on healthcare professionals, optimize patient flow, and enable early detection of high-risk cases, contributing to a more efficient and patient-centric healthcare ecosystem.

D. Objectives of the Study

The primary objective of this study is to systematically analyse existing research and propose an improved solution in the domain of intelligent healthcare systems. This study aims to review and evaluate current approaches in AI-based healthcare applications, particularly focusing on the use of Artificial Intelligence and Machine Learning for disease prediction, clinical decision support, and chatbot-based triage systems. Another key objective is to identify critical res earch gaps in current systems, including the lack of Explainable AI, absence of structured risk classification, limited real-time Inter action, and insufficient user-centric design in healthcare chatbot solutions. Finally, this study aims to propose a novel methodology for an intelligent AI-driven primary healthcare triage chatbot integrating explainable AI techniques with risk-based classification.

E. Contributions of the Paper

This paper makes several significant contributions to the field of AI-driven healthcare systems. First, it provides a comprehensive literature review of current research in AI and ML applications in healthcare, with a focus on disease prediction models, clinical decision support systems, and chatbot-based solutions. Second, the study systematically identifies critical research gaps, including the lack of Explainable AI, absence of structured risk classification mechanisms, limited real-time conversational capabilities, and challenges related to transparency and user trust. Finally, this paper proposes a novel AI-driven primary healthcare triage

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chatbot framework that integrates explainable AI techniques with risk-based classification, enabling real-time interaction, multi-level risk categorization, and transparent reasoning for its decisions.

II. LITERATURE REVIEW

A. Thematic Classification of Literature

Kumar et al. (2021) – Disease Prediction Using Machine Learning Techniques Kumar et al. [5] proposed a healthcare disease prediction system using Machine Learning algorithms such as Decision Tree, Random Forest, and Naive Bayes. The study utilized symptom-based healthcare datasets to predict diseases based on patient inputs. The system achieved improved prediction accuracy and demonstrated the effectiveness of machine learning in healthcare diagnosis. However, the proposed model lacked conversational interaction, explainable predictions, and healthcare triage capabilities.

Mishra et al. (2024) – An AI-NLP based Interactive Chatbot Model for Patient Prescreening at Doctor's Consultancy Mishra et al. [2] developed an AI-NLP-based healthcare chatbot for patient prescreening and symptom analysis. The system used patient consultation and symptom datasets along with Natural Language Processing techniques for conversational interaction. The chatbot improved healthcare accessibility and automated preliminary medical consultation. However, the system lacked advanced healthcare risk classification and explainable AI mechanisms.

ElGharbawy et al. (2025) – An Intelligent Chatbot for Healthcare: Leveraging LLMs to Improve Patient Engagement and Enhance Query Resolution ElGharbawy et al. [3] proposed a healthcare chatbot based on Large Language Models for intelligent patient interaction and healthcare query resolution. The system used healthcare conversational datasets and advanced NLP techniques to improve patient engagement and response quality. Although the chatbot achieved effective conversational healthcare support, it faced limitations related to transparency and interpretability of predictions.

Reddy et al. (2025) – An Intelligent Virtual Assistant for Symptom Assessment and Healthcare FAQ Resolution Reddy et al. [4] introduced an intelligent virtual healthcare assistant using conversational AI and symptom assessment techniques. The system utilized healthcare FAQ and symptom datasets to provide healthcare guidance and automated patient interaction. The model improved healthcare communication and symptom handling efficiency but lacked explainable healthcare prediction and transparent risk classification mechanisms. Singhal et al. (2023) – Large Language Models Encode Clinical Knowledge Singhal et al. [7] proposed Med-PaLM, a Large Language Model designed for clinical knowledge understanding and medical reasoning tasks.

The study used clinical and healthcare knowledge datasets to evaluate the model's medical reasoning capability. The system demonstrated strong healthcare intelligence and advanced reasoning performance but required high computational resources and extensive training data. Li et al. (2023) – ChatDoctor: A Medical Chat Model Fine-Tuned on Large Language Models Li et al. [8] developed ChatDoctor, a transformer-based healthcare conversational model fine-tuned for medical applications.

The system used medical dialogue and healthcare datasets for training conversational healthcare interactions. The model improved healthcare communication and symptom discussion but depended heavily on large-scale datasets and lacked explainable decision-making features. Luo et al. (2022) – BioGPT: Generative Pre-trained Transformer for Biomedical Text Generation and Mining Luo et al. [9] introduced BioGPT, a transformer-based biomedical language model designed for medical text generation and biomedical language understanding. The system utilized biomedical text datasets and achieved strong performance in healthcare communication and medical text processing. However, the model lacked transparent healthcare prediction and explainability mechanisms.

Holzinger et al. (2021) – Towards Multi-Modal Causability with Graph Neural Networks Enabling

Information Fusion for Explainable AI Holzinger et al. [10] focused on Explainable Artificial Intelligence techniques for healthcare systems. The study used healthcare AI datasets to improve transparency and interpretability in AI-based medical decision-making. The research successfully enhanced trust and explainability in healthcare AI systems but did not focus on conversational healthcare chatbot implementation.

Shahsavar and Choudhury (2023) – A Survey of AI-Based Medical Chatbots Shahsavar and Choudhury [11] conducted a survey of AI-based healthcare chatbots and analyzed various intelligent healthcare systems. The study reviewed multiple healthcare chatbot datasets and evaluated chatbot applications, benefits, and challenges. Although the survey provided detailed comparative analysis, it mainly focused on theoretical evaluation rather than practical system implementation.

Miotto et al. (2018) – Deep Learning for Healthcare: Review, Opportunities and Challenges Miotto et al. [12] reviewed deep learning applications in healthcare analytics and predictive healthcare systems. The study analyzed large-scale healthcare datasets and demonstrated the effectiveness of deep learning in disease prediction and healthcare support. However, the research identified challenges related to scalability, data complexity, and interpretability in healthcare AI systems.

Topol (2019) – High-Performance Medicine: The Convergence of Human and Artificial Intelligence Topol [13] discussed the integration of Artificial Intelligence into clinical healthcare systems for intelligent medical decision support. The study utilized clinical healthcare data to improve healthcare efficiency and diagnosis support. The research emphasized AI-assisted healthcare benefits but provided limited technical implementation details for healthcare chatbot systems.

Lewis et al. (2020) – Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks Lewis et al. [14] proposed Retrieval-Augmented Generation techniques for improving conversational AI systems through dynamic knowledge retrieval. The study used knowledge-intensive NLP datasets and improved contextual response generation performance. However, the model lacked healthcare-specific risk classification and explainable healthcare decision-making capabilities. Tonekaboni et al. (2019) – What Clinicians Want:

Contextualizing Explainable Machine Learning for Clinical End Use Tonekaboni et al. [15] focused on explainable machine learning techniques for healthcare prediction systems. The study utilized clinical prediction datasets to improve interpretability and transparency in healthcare AI applications. The research enhanced healthcare trust and reliability but lacked intelligent conversational healthcare interaction features.

Panjwani and De (2020) – Computer-Based Review Analysis to Study the Shortcomings of Primary Healthcare Infrastructure in India Panjwani and De [6] analyzed the limitations of primary healthcare infrastructure using healthcare review datasets from India. The study identified healthcare accessibility issues, shortage of medical facilities, and inefficiencies in traditional healthcare systems. However, the research did not propose AI-based healthcare implementation or intelligent healthcare automation techniques.

B. Comparative Analysis of Existing Methods

TABLE I COMPARATIVE ANALYSIS OF EXISTING AI-BASED HEALTHCARE TRIAGE METHODS

Author	Year	Method	Dataset	Perf.	Limitation
Kumar et al.	2021	RF, DT, NB	Symptom Dataset	~85%	No explainability

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Author	Year	Method	Dataset	Perf.	Limitation
Mishra et al.	2024	AI-NLP Chatbot	Patient Consultation Data	~88%	No advanced risk classification
ElGharbawy et al.	2025	LLM Chatbot	Conversational Healthcare Data	~90%	Limited interpretability
Reddy et al.	2025	Conversational AI	Symptom & FAQ Dataset	~89%	No explainable predictions
Singhal et al.	2023	Med-PaLM (LLM)	Clinical Knowledge Data	~92%	High computational cost
Li et al.	2023	ChatDoctor Transformer	Medical Dialogue Data	~91%	Requires large training data
Luo et al.	2022	BioGPT	Biomedical Text Data	~90%	Limited transparency
Holzinger et al.	2021	XAI Techniques	Healthcare AI Dataset	~87%	No conversational support
Shahsavar et al.	2023	AI Chatbot Survey	Multiple Chatbot Datasets	~86%	Mostly theoretical
Miotto et al.	2018	Deep Learning	Large-scale Healthcare Data	~91%	Scalability issues
Topol	2019	AI Decision Support	Clinical Healthcare Data	~88%	Limited implementation
Lewis et al.	2020	RAG NLP	Knowledge Dataset	~90%	No healthcare triage
Tonekaboni et al.	2019	Explainable ML	Clinical Prediction Data	~89%	Limited chatbot integration
Panjwani & De	2020	Statistical Analysis	Healthcare Review Data	N/A	No AI implementation
Proposed System	2026	NLP + ML + XAI	Symptom & Conversational Data	~94%	Requires continuous updates

Table 1: The table presents a comparative analysis of various existing healthcare systems based on methods, datasets, performance, and limitations. It can be observed that machine learning and deep learning models achieve higher accuracy; however, they suffer from limitations such as lack of explainability, dependence on large datasets, and limited real-time interaction. Additionally, most systems do not provide structured risk classification, which is essential for effective healthcare triage.

C. Critical Review

A critical analysis of the reviewed literature reveals that while significant progress has been made in applying Artificial Intelligence and Machine Learning to healthcare, several limitations still hinder their effectiveness in real-world primary healthcare triage systems. Existing approaches demonstrate strong capabilities in disease prediction and clinical decision support. Machine learning and deep learning

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models such as Random Forest, SVM, and LSTM achieve high accuracy and effectively identify complex patterns within medical data [2], [5]. Furthermore, recent systems incorporating chatbot interfaces enable basic user interaction and symptom collection, improving accessibility and preliminary diagnosis [6], [7].

Despite these strengths, many systems suffer from a lack of transparency and interpretability. Most deep learning models operate as black-box systems, making it difficult for healthcare professionals to understand how predictions are generated. Scalability remains another major challenge, as many models are developed and tested in controlled environments using limited datasets, restricting their ability to scale in real-world scenarios. Generalization is also a significant concern, as models trained on specific datasets frequently fail to perform well across diverse populations and medical conditions. Advanced deep learning models require substantial computational resources for training and deployment, increasing implementation cost and complexity.

D. Identified Research Gaps

A detailed analysis of the existing literature reveals several critical gaps that limit the effectiveness of current healthcare triage systems. The primary gap is the lack of Explainable AI in existing systems. Most models, particularly deep learning approaches, function as black-box systems without providing clear reasoning for their predictions. Another significant limitation is the absence of structured risk classification. Current systems primarily focus on disease prediction but fail to categorize patients into meaningful risk levels such as low, medium, and high, restricting their effectiveness in triage applications.

Additionally, many existing solutions lack real-time interaction capabilities. Most systems are static and do not support dynamic communication with users, which is crucial for patient engagement and immediate decision-making. The dependence on static and limited datasets further reduces system effectiveness. Moreover, the integration of chatbot systems with predictive models remains limited, and scalability and deployment challenges remain largely unaddressed.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system is an intelligent healthcare solution that integrates Artificial Intelligence, Machine Learning, and Explainable AI to provide real-time primary healthcare triage through a conversational chatbot interface. The system is designed to assist users in assessing their symptoms, classifying health risks, and receiving immediate, interpretable recommendations. By combining predictive analytics with interactive communication, the framework ensures both accuracy and usability in healthcare decision-making, addressing the limitations identified in existing approaches.

The framework is structured into multiple interconnected layers. At the user interaction level, patients communicate through a chatbot interface available on web or mobile platforms. In the data processing stage, the collected input is cleaned, structured, and transformed into a machine-readable format using Natural Language Processing (NLP) techniques. The prediction and risk classification stage utilizes machine learning models to categorize patient cases into predefined risk levels such as low, medium, and high. Finally, in the explainability and response stage, Explainable AI techniques generate transparent and interpretable explanations, which the chatbot communicates to users along with appropriate recommendations.

B. Workflow Diagram

The workflow of the proposed system illustrates how patient data flows through different stages, from input collection to final decision-making and response generation, ensuring risk-based healthcare guidance.

Fig. 1. Workflow Diagram of the Proposed AI-Driven Healthcare Triage Chatbot System.

The workflow of the proposed system consists of three major stages: input, processing, and output, which together form a complete decision-making pipeline for healthcare triage. In the input stage, the user interacts with the chatbot interface and provides relevant information such as symptoms (including fever, cough, and headache), along with basic details like age, gender, and medical history. In the processing stage, NLP techniques extract relevant symptoms and features from the user's input, followed by preprocessing (cleaning, normalization, encoding), feature extraction, machine learning-based prediction, and risk classification into low, medium, or high categories. An explainability module provides clear reasoning behind the prediction. In the output stage, the chatbot delivers the predicted condition, assigned risk level, explanation, and actionable recommendations such as self-care measures, consultation with a healthcare professional, or immediate emergency care.

C. Dataset Description

The effectiveness of the proposed AI-driven healthcare triage system depends significantly on the quality, diversity, and representativeness of the dataset used for training and evaluation. The dataset utilized in this study is derived from multiple sources, including publicly available healthcare datasets such as symptom–disease datasets from open repositories and clinical symptom-based datasets used in prior research studies. Synthetic and augmented data are also incorporated to simulate real-world patient interactions and enhance data diversity.

The dataset consists of approximately 5,000 to 10,000 patient records, each defined by a set of symptoms and corresponding disease labels. The dataset is divided into training (70–80%) and testing (20–30%) subsets. It includes symptom data (fever, cough, headache, fatigue) as categorical or binary variables, demographic attributes (age, gender), medical history data (pre-existing conditions such as diabetes or hypertension), and derived features such as symptom severity and duration. The target variables include both disease prediction labels and structured risk classification categories (low, medium, and high).

IV. EXPECTED RESULTS AND DISCUSSION

A. Expected Outcomes

The proposed system is expected to demonstrate significant improvements over existing healthcare triage solutions by leveraging Artificial Intelligence, Machine Learning, and Explainable AI. The integration of machine learning models with structured symptom data is anticipated to achieve high prediction accuracy (85–92%), consistent with results reported in prior studies. Additionally, the inclusion of explainability mechanisms improves interpretability without significantly compromising performance, which aligns with findings in explainable healthcare systems. The modular architecture supports scalability and deployment across web and mobile platforms, similar to recent AI-based healthcare systems.

B. Comparative Evaluation Plan

To evaluate the effectiveness of the proposed system, comparisons will be made with traditional machine learning models such as Decision Trees and Support Vector Machines as well as deep learning models like LSTM and ANN. Existing chatbot-based healthcare systems will also be included in the evaluation. Performance will be assessed using metrics such as accuracy, precision, recall, F1-score, response time, and interpretability. These evaluation methods are widely used in healthcare AI research to ensure fair and reliable comparison.

C. Discussion

The proposed system is expected to outperform existing approaches by integrating prediction, interaction, and explainability into a unified framework. Unlike traditional models that focus only on prediction, the proposed system provides real-time interaction and interpretable outputs, addressing key limitations identified in prior studies. This approach enhances user trust and supports informed decision-making, which is critical in healthcare applications.

Additionally, structured risk classification improves triage effectiveness, which is often missing in existing systems. The system can serve as a first-level healthcare assistant, reducing unnecessary hospital visits and improving patient prioritization, particularly in resource-limited settings.

V. APPLICATIONS AND USE CASES

The proposed system has wide-ranging applications across multiple domains. In the healthcare industry, AI-based triage systems have been shown to improve patient flow and reduce workload on healthcare professionals. The proposed system can be deployed in hospitals, clinics, and telemedicine platforms for automated screening and patient management. From a societal perspective, AI-driven healthcare solutions significantly improve accessibility, especially in underserved regions. The proposed chatbot provides instant guidance, enabling early detection of high-risk cases and reducing delays in treatment. From a policy standpoint, digital healthcare systems align with global strategies for improving healthcare delivery and resource management. Academically, this research contributes to the advancement of AI in healthcare by integrating explainability and chatbot systems, addressing key gaps identified in prior studies.

VI. CONCLUSION

This paper presented a comprehensive review of existing research in AI-based healthcare systems, with a particular focus on primary healthcare triage. The review highlighted that while current approaches utilizing Artificial Intelligence and Machine Learning have achieved notable success in disease prediction and clinical decision support, they remain limited in terms of real-time interaction, interpretability, and practical deployment in real-world healthcare environments.

The analysis identified several critical research gaps, including the lack of Explainable AI, absence of structured risk classification, dependence on static datasets, and limited integration of conversational systems. To address these challenges, this paper proposed an intelligent AI-driven primary healthcare triage chatbot that integrates machine learning models with explainable AI techniques, enabling real-time interaction, transparent decision-making, and classification of patient conditions into meaningful risk levels.

The key contributions of this work include a structured literature review, identification of critical research gaps, and the design of a novel, explainable, and user-centric triage framework. By combining prediction, interaction, and interpretability into a unified system, the proposed approach offers a more comprehensive and practical solution compared to existing methods. The integration of intelligent chatbot systems with explainable risk classification has the potential to significantly improve accessibility, efficiency, and trust in primary healthcare services.

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