

A Framework for AI-Driven Health Triage to Improve Healthcare Access and Affordability in Low- and Middle-Income Countries (LMICs)

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Healthcare Crisis in LMICs



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9.9 doctors, nurses & mid-wives/**10,000** people, lower than global median of 48.6 (WHO Standard **1:3:5**, While in Bangladesh **1:0.7:0.7**)

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Most people don't know where to go to seek healthcare; **absent of triage and referral system.**

~ **65%** of the population get healthcare from **informal sector**



Leading to misinformation, diagnostic delays, and delayed care



In Bangladesh **67.3%** of antibiotic dispenses from unqualified providers without prescriptions



63% people

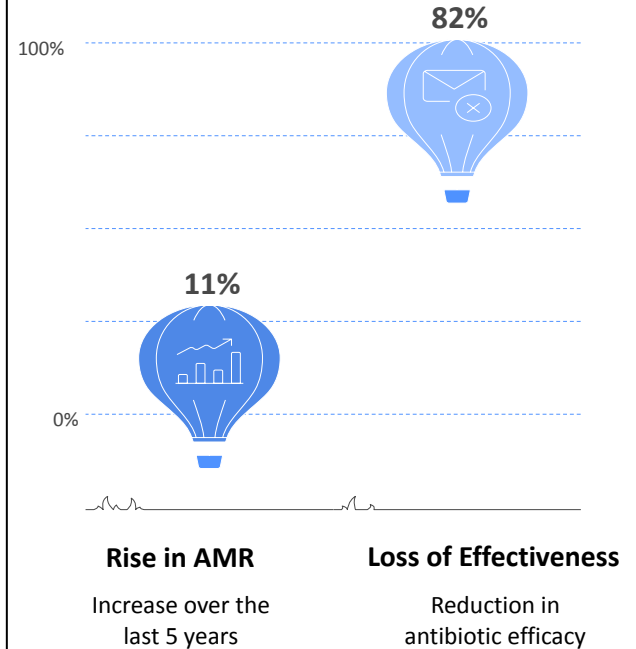
Self-medicate with antibiotics drives antimicrobial resistance in LMICs

Healthcare Crisis in LMICs

45% of Bangladeshis are resistant to at least one antibiotic;

AMR causes **1.27M** yearly deaths, projected to reach 10M by 2050

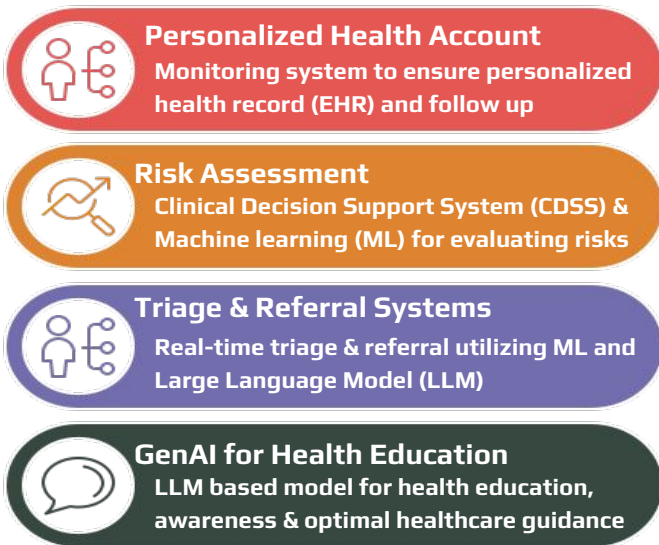
Antimicrobial Resistance (AMR) in Bangladesh



AI to Transform Healthcare for Risk Assessment, Triage & Referral Systems

An AI powered clinically validated health risk assessment, triage & referral systems can empower individuals to navigate right healthcare at the right time

AI Engine



Inclusive Design



Multilingual Capability

Supports Bangla, Banglish, and English

Clinically Validated Dataset and AI Engine

Knowledge base for health education, disease symptoms and risk assessment

Low Bandwidth Optimization

Designed for both urban and rural areas (online & offline)

AI to Transform Healthcare for Risk Assessment, Triage & Referral Systems



Accessible, Affordable & Quality Healthcare

AI powered risk assessment, triage and referral systems that delivers immediate and trustworthy guidance, empowering users to make **healthcare decisions anytime, anywhere**



Medicine Adherence

Promoting **responsible medication practices**, offer AI-driven guidance that helps users understand and follow prescribed treatments, **improving adherence and reducing AMR**



Health Education and Awareness

GenAI based medical chatbot designed to address health education and awareness for a healthy living and **reducing stigma and taboo**



Optimal AI-Driven Platform

AI-driven, **clinically validated** and **evidence-based support** that empowers both **users and providers** to make safer, cost-effective health decisions and follow up

This research addresses critical gaps in healthcare delivery in low- and middle-income countries, where timely triage improves patient outcomes.

Methodology

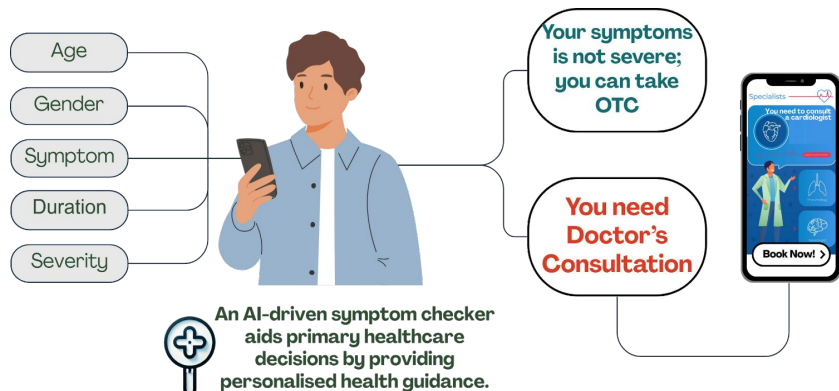
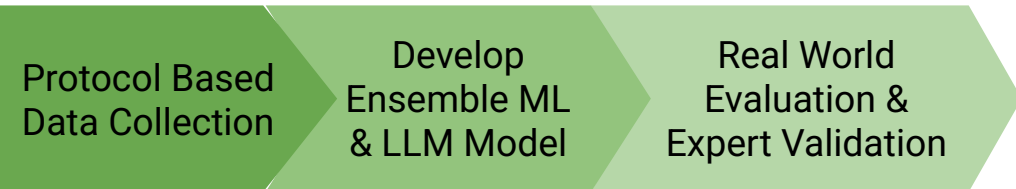


Figure: AI based symptom checker to assess based on user data and provides personalized recommendations for doctor consultations or OTC medications



Model training

- Converted structured patient data into clinical narratives to enable contextual processing by ML & LLM models



Evaluation

- Compared an ML ensemble and three LLM backbones (BERT, ClinicalBERT, DeBERTa) to find the best AI approach for both accuracy and contextual understanding



Real-World Performance Benchmark

- Evaluated on real-world patient narratives collected from local pharmacies



Clinical Validation

- Utilized a multi-physician consensus as the clinical standard to measure practical effectiveness and safety in decision making

Methodology: Clinically Validated Dataset

Table: Detailed information of dataset attributes

	Attribute	Type	Description
In put	Gender	Categorical	Male, Female
	Age	Categorical	Male: ≤5, 6–15, 16–60, >60 years Female: ≤5, 6–15, 16–45, >45 years
	Duration	Categorical	≤3 days, >3 days
	Symptoms	String	1,816 unique symptoms with combinations for disease conditions
	Severity	Categorical	Mild: No interference with daily activities Moderate: Some daily activities are interrupted Severe: Cannot perform any daily activities
Out put	Decisions	Categorical	Referral for Doctor consultation or OTC medication and management

Building the Medical Knowledge Base

Curated a medical knowledge base of prevalent diseases and symptoms **from trusted national and global health sources with clinical validation**

Creating Patient Cases

Generated **130,637 unique scenarios**, representing a combination of all possible patient presentations based on symptoms, demographics, duration, and severity

Symptom Standardization

The Symptom Standardization Pipeline used NLTK to clean text, merge similar terms, lemmatize (e.g., "sneezing" → "sneeze"), and simplify medical jargon

Dataset Validation

Each case was reviewed and **validated by a panel of three physician teams** to ensure clinical accuracy for AI model benchmarking

Methodology: Models

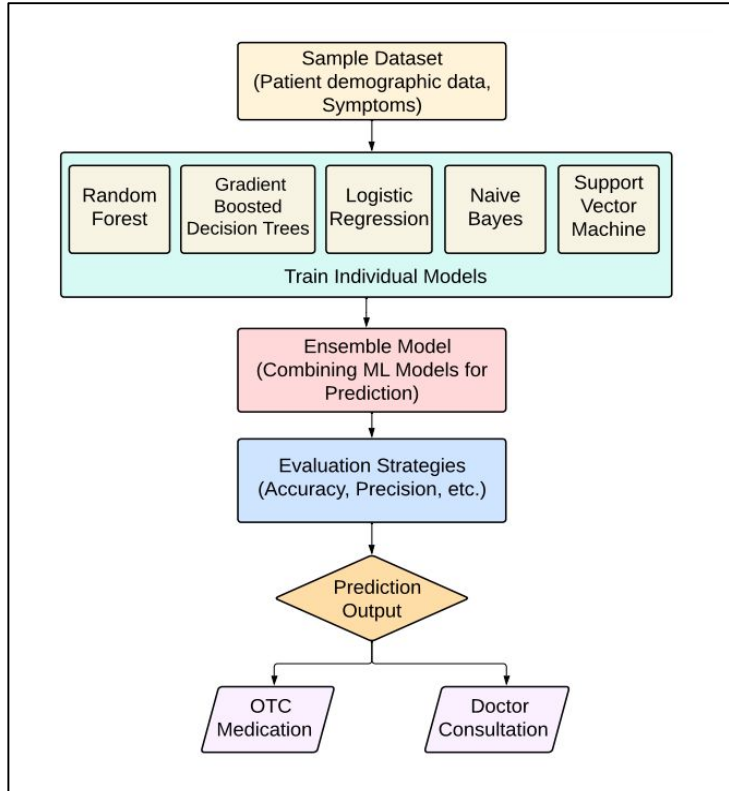


Figure: Ensemble machine learning approach for recommending healthcare pathways

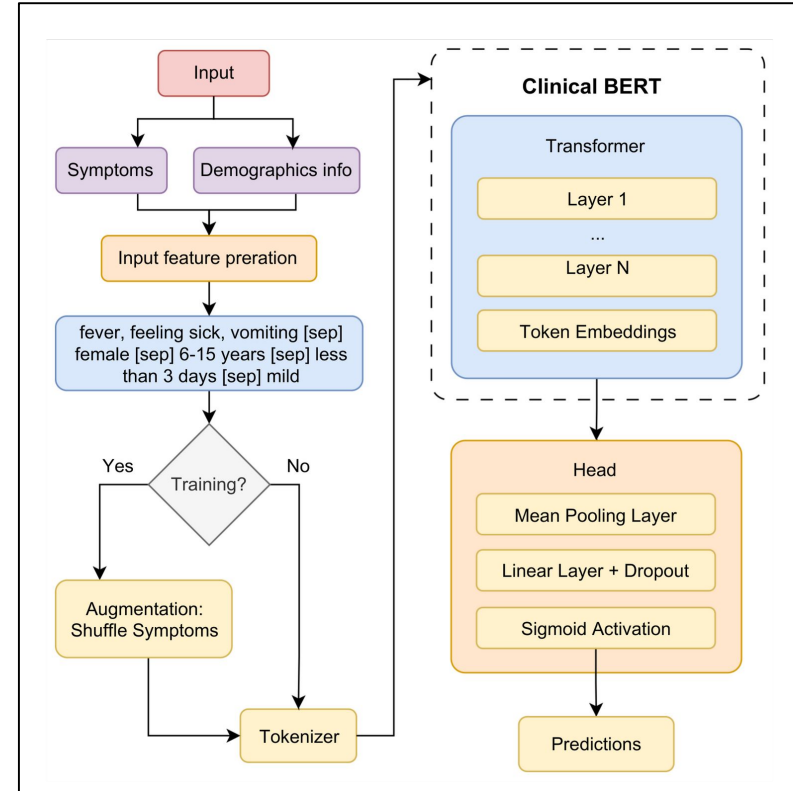


Figure: GenAI approach for recommending healthcare pathways

Evaluation Results



247

A evaluation set of 247 patient narratives was collected from local pharmacies to test real-world performance.

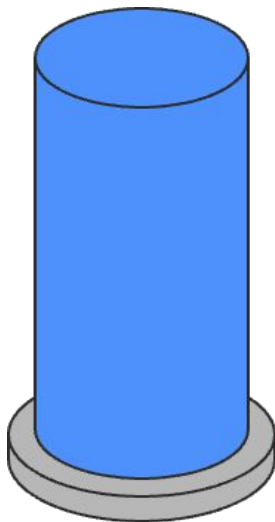
Ensemble Machine Learning

Input: Structured Clinical Data

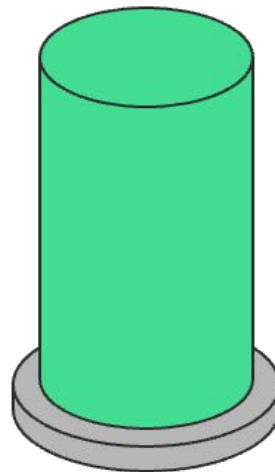


Soft-voting ensemble model combined algorithms for superior predictive performance

94.6%



81.0%



Fine-Tuned Large Language Models

Input: Unstructured Patient Narratives



BERT with data augmentation performed highest among LLMs, but lower than the ensemble

❑ **Key Finding:** ML ensemble shows higher accuracy than LLM, highlighting structured data's value for predictive triage

Transforming Healthcare Delivery with Susastho.AI

SuSastho.AI, digital healthcare platform for transforming healthcare risk assessment, triage and referral systems towards establishing accessible, affordable, quality healthcare for all



Digital Front Door

Complete digital health ecosystem providing immediate guidance for populations with limited healthcare access



Core Engine

Clinically-validated AI model serving as the central Risk Assessment & Referral Engine, processing symptoms accurately



Intelligent Triage System

Advanced engine analyzes user input for critical triage, guiding patients to telemedicine, clinics, or OTC solutions



Population Health Impact

Combats antimicrobial resistance by interrupting self-medication, providing data for public health planning

- ❑ **Transformative Outcome:** This integrated approach creates a scalable foundation for equitable healthcare delivery, combining patient guidance with population health intelligence.

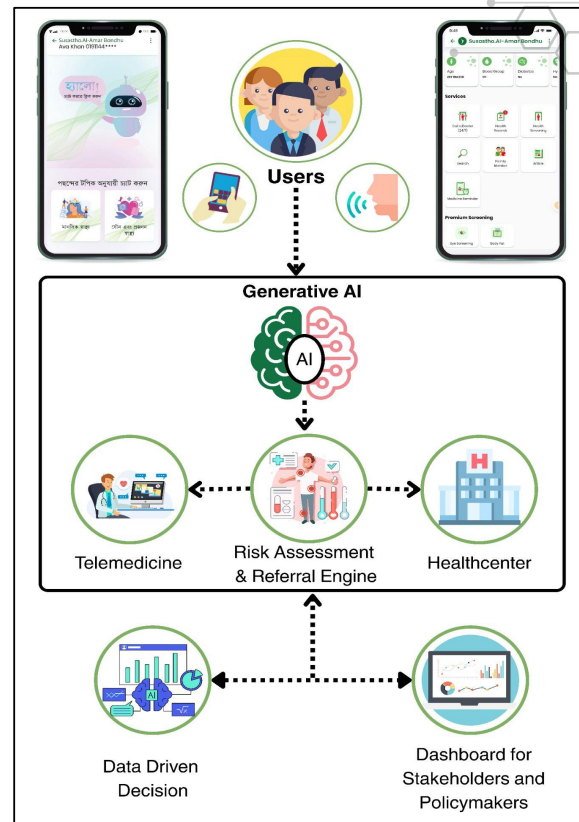


Figure: The SuSastho.AI Ecosystem's central AI engine processes user inputs to guide patients to the correct care pathway and provides data-driven insights for public health stakeholders

End-to-End System Architecture

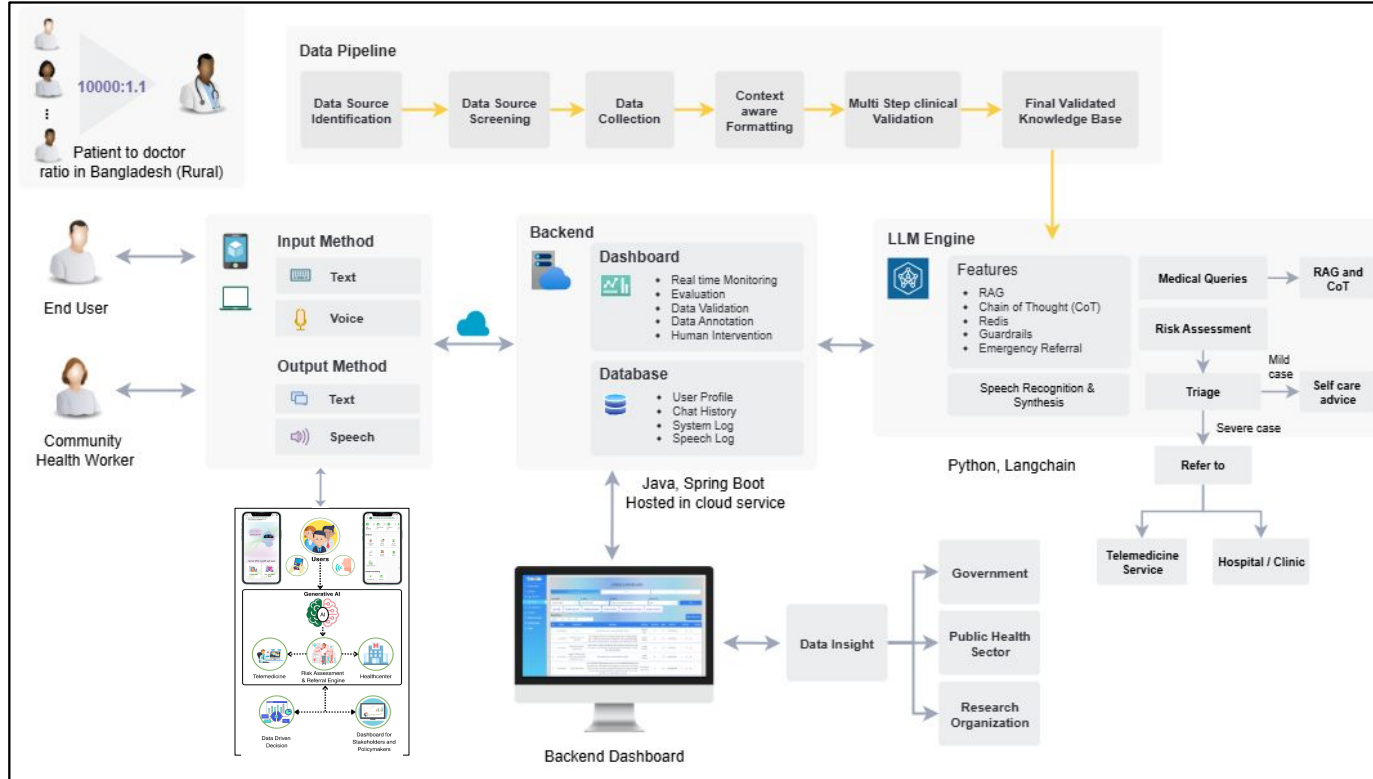


Figure: The Complete Triage Pipeline Leveraging a Hybrid AI Framework for Integration with the Susastho.AI Digital Health Ecosystem

Socio-economic IMPACT



Empowering Primary Healthcare

Empowering primary healthcare decisions with recommendations for OTC medications or doctor consultations



Addressing Drug Misuse

Addressing self-medication and irrational antibiotic use to combat misuse



Cost Reduction

Reducing healthcare costs by optimizing medication usage and preventing unnecessary doctor visits through accurate and timely decisions



Long-term Financial Relief

Mitigates future healthcare expenditures by addressing antibiotic resistance early, potentially saving billions in long-term costs

Challenges & Limitations



01

Demographic Bias & Contextual Adaptation

This solution risks demographic bias and may fail to adapt to local context like dialects, cultural symptom descriptions, and regional healthcare realities.

02

Resource Constraints

Training LLMs requires significant computational power and specialized hardware, often unavailable in target deployment environments.

03

Validation Funding

Expanding real-world validation to large, multi-demographic studies for safety and generalizability requires substantial funding.

Future Work & Strategic Roadmap



01	Deploy and Pilot the Hybrid Architecture	Deploy the hybrid system in a large-scale pilot with CMED Health to validate its real-world impact
02	Achieve Data Equity and Inclusivity	Expand datasets with diverse demographics to build a more balanced and representative model
03	Develop Advanced Health Risk Prediction	Evolve the AI from immediate triage to proactively forecasting future health risks, enabling a shift towards preventative care
04	Integrate Proactive Health Tracking	Implement a long-term monitoring system for effective management of NCD patients and maternal care
05	Optimize for Accessibility	Investigate lightweight LLM architectures to ensure real-time performance and usability in LMIC (online & offline)

Conclusion



Clinically Accurate and Safe Guidance

ML model achieves 94.6% accuracy, providing reliable clinical recommendations



Immediate Access to Quality Care

Empowers confident health decisions by providing instant, trustworthy triage when a doctor is inaccessible



Promoting Rational Medicine Use

Solution prevents self-medication by guiding safe antibiotic use and promoting responsible care



Technology-Enabled Health Equity

Promotes health equity by enabling early action, reducing care barriers, and empowering Community Health Workers with reliable tools



A viable path to Universal Health Coverage and SDGs ensures equitable healthcare access for all.





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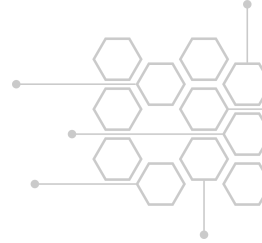


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*Healthcare is not just a service,
it's a human right. Let's deliver it
together*

Thank you!