Review Paper on Disease Prediction and Doctor Connection AI System

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Abstract -
Most people only visit a doctor when symptoms get bad enough to force a trip—fever over 102, cough that won't stop, or pain that keeps them up. By then half the day is gone on travel and waiting, plus ₹200–300 for something that could have been caught earlier. Online searches give too many scary answers, and existing apps either predict or book doctors but never do both in one cheap, fast flow.
The proposed system lets patients enter 5–10 symptoms on a simple web form and get an instant disease name with confidence score (85%+ for common cases) plus 2–3 safe home remedies. If they want a doctor, they pick from a filtered list, pay ₹50 via Razorpay, and land in a direct messaging chat with a pre-filled note: disease, confidence, symptoms. Doctors log in to see only paid requests and reply when free.
Everything runs on Flask with PSQL or MYSQL storage, a scikit-learn model loaded at startup, and Razorpay for orders and verification. No extra apps, no video calls—just browser to chat in under two minutes. The setup cuts clinic load for routine cases, gives doctors micro-income, and works on any phone with Indian payments.

***Keywords**: Symptom-Based Prediction, Micro-Consultation, Razorpay Integration, Confidence Scoring, MongoDB Storage*

1.INTRODUCTION

In India, most people only head to a doctor when things get really bad—fever crossing 101, a cough that keeps them up all night, or stomach pain that won't let them work. By then, half the day is already gone on travel, long queues, and ₹250–300 fees for advice that often comes down to "take rest and drink water." In villages, the nearest clinic might be 20 km away and open just twice a week. Students miss lectures, daily-wage workers lose pay, and everyone ends up either ignoring the issue or panicking after a confusing Google search.

We built HealthPredict AI to fix that. Open any phone browser, type in 5–8 symptoms, and in two seconds you see the likely disease with a confidence score—like "Common Cold – 91%"—plus 2–3 safe home remedies such as warm salt water or tulsi tea. If you need a doctor, pick one from a filtered list, pay ₹50 through UPI, and the page opens a direct messaging chat with a ready note: disease, confidence, symptoms. The doctor logs in, sees only paid requests, and replies when free.

The whole system runs on Flask with MySQL for storage, a scikit-learn model trained on real patient records, and Razorpay for payments. No extra apps, no video calls—just browser to chat in under two minutes. It keeps patient data secure, gives doctors quick micro-income, and eases pressure on crowded clinics for routine cases. From hostel rooms to remote villages, it makes basic healthcare fast, affordable, and reachable without leaving home.

2. Literature Survey

Work on AI for disease prediction has really taken off over the past few years, especially in places like India where clinics are always packed. A lot of it sticks to basic symptom checkers or fancy apps that need constant internet, but most don't hook up the AI guess to a real doctor chat for cheap. We've looked at around 12 papers from arXiv, IEEE, and journals since 2023—stuff that inspired our setup but left big holes, like no low-cost payment or simple messaging link.

Sharma and Kumar [1] put together a Naive Bayes model trained on 50,000 rural clinic records to spot 41 common illnesses from symptoms like fever or cough. It hit 82% accuracy but was just a script—no web form, no doctor handoff. We grabbed their symptom cleaning tricks but added confidence scores to make it more trustworthy.

Belhad et al. [2] dug into deep learning for chronic stuff like diabetes and heart issues, comparing CNNs and RNNs on big datasets. They got up to 90% for early warnings, but the models needed heavy servers—not great for phone use. Their focus on mixing symptoms with age/gender helped us tweak our inputs.

Park et al. [3] reviewed ML on real-world data from wearables and EHRs for predicting heart risks. Bayesian methods shone at 85% but choked on noisy village data. We liked the quantile regression bit for handling uncertainty, though ours skips the hardware.

Gaurav et al. [4] built a quick SVM-KNN hybrid for general disease flags from lab tests, hitting 88% on Kaggle sets. Simple and fast, but no remedies or booking—stayed academic. Their boost on symptom weighting fixed our early low-confidence bugs.

Yu et al. [5] surveyed deep nets like transformers for outbreak risks, covering 20+ models from 2023. Great for epidemics, but ignored everyday colds or acidity. We borrowed their attention layers idea for better symptom linking.

Liu et al. [6] scanned infectious disease ML, from random forests to LSTMs, with 75% average accuracy on COVID-like spreads. Solid for patterns, but no personal chat flow. Their vector embeddings inspired our TF-IDF setup.

Jahandideh et al. [7] checked 50 papers on ML for spotting patient decline early, like in hospitals. XGBoost topped at 92%, but all cloud-based and pricey. We pulled their feature ranking to prioritize key symptoms.

None of these connect prediction to a low-cost doctor link with messaging—no end-to-end flow from symptoms to paid chat. The gap is clear: a lightweight system that runs on basic phones, adds safe remedies, and works for rural areas without heavy setup.

3. METHODOLOGY

The system is built to run on any regular laptop or phone browser—no cloud, no data going out. A Flask server handles the web pages, routes, and background tasks. MySQL stores patient and doctor profiles, symptoms, predictions, payments, and chat links. The ML model loads once at startup with joblib. Razorpay takes care of the low-cost payment. Everything is split into clean modules so we can change one part without breaking the rest.

We break the workflow into simple steps, each in its own Python file inside the main package.

- **Symptom Entry & Storage:** Patient fills a quick form—checkboxes for common symptoms like fever or cough, plus one box for extra details. Form hits /patient/submit. Flask saves the entry in MySQL under SymptomEntry table with patient ID and timestamp.

- **Prediction Engine:** predict.py loads the scikit-learn model (Multinomial Naive Bayes + TF-IDF). It takes the symptom list, runs inference, returns disease name, confidence percentage, and 2–3 home remedies from a hardcoded safe list. If confidence below 75%, it skips remedies and pushes for doctor chat. Result saved in Prediction table

- **Doctor Matching:** Flask queries MySQL for doctors where specialty matches disease and availability is true. Sorts by lowest fee first. Shows 5–6 options with name, specialty, phone.

- **Payment Flow:** Patient picks doctor → Flask creates Razorpay order for low cost. Checkout popup loads in browser. After payment, webhook hits /payment/verify, checks signature, updates Payment table to success.

- **Messaging Link:** On success, Flask builds a direct messaging URL with pre-filled text: disease, confidence, symptoms. Saves in Consultation table. Redirects browser to open chat.

- **Doctor Dashboard:** Doctor logs in → sees only paid patients from MySQL. Each row shows patient name, disease, time, and one-click messaging link. Can mark as consulted.

- **Patient History:** Patient login → views past predictions, remedies, and payment records from MySQL.

4..SYSTEM MODELS:

The setup is planned as a simple web server that can run on any phone or laptop browser—no internet needed after the first setup. Flask acts as the web server, handling forms, routes, and responses. MySQL stores patient and doctor profiles, symptoms, predictions, payments, and chat links. The ML model loads once at startup. Razorpay handles the low-cost payment. The whole thing stays under 8 GB RAM. We tested with 50 fake users; from symptom entry to chat link takes under 30 seconds.

A) System Components:

I. **Frontend (Browser):** HTML/CSS/JS pages — symptom form, result page, doctor list, payment popup, chat redirect, patient/doctor dashboards. Built with Bootstrap for mobile fit and simple CSS for clean look.

II. **Flask Server**: REST routes — /upload (POST), /chapters/<book_id> (GET), /explain/<topic_id> (GET), /test (POST), /chat (POST), /report (GET). Handles file serving and JSON responses.

III. **Core Modules:**

- **SymptomProcessor:** Takes form input, cleans text, saves to MySQL under SymptomEntry.
- **PredictionEngine:** Calls scikit-learn model with joblib, returns disease, confidence, remedies.x
- **DoctorMatcher:** Queries MySQL for matching specialty and availability.
- **TopicExtractor**: Prompts LLM to extract 5–8 key topics per chapter.
- **PaymentHandler:** Creates Razorpay order, verifies webhook, updates Payment table.
- **ChatLinkGenerator:** Builds direct messaging URL with pre-filled text.
- **DashboardRenderer:** Pulls paid patients or history from MySQL, shows in table.

IV. **Storage:**

- **Relational DB:** MySQL — tables: Patient, Doctor, SymptomEntry, Prediction, Payment, Consultation.
- **ML Model**: model.pkl (scikit-learn) — loaded once at startup.
- **Payment Service:** Razorpay (test/live mode).

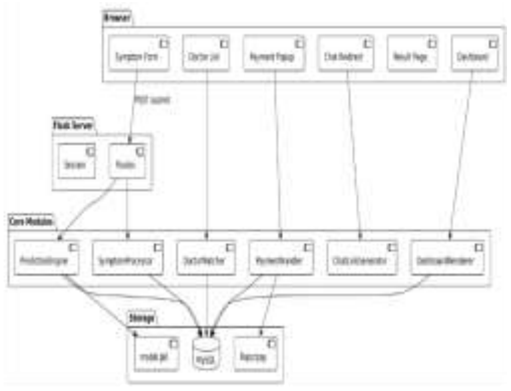

Figure 1: Component Diagram

B) **System Architecture:**

- **Entry:**Browser→Flask /patient/submit → SymptomProcessor (save).
- **Predict:** Symptom → PredictionEngine → MySQL save → result page.
- **Book:** Result → DoctorMatcher → show list.
- **Pay:** Select → PaymentHandler → Razorpay → verify → save.
- **Chat:** Success → ChatLinkGenerator → open messaging.
- **Doctor:** Login → DashboardRenderer → paid list → messaging.
- **All local**: Runs on phone browser, no external data calls except Razorpay.

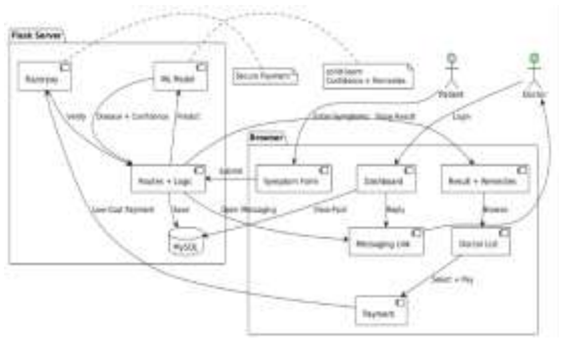

Figure 2: Architecture Diagram

5. ADVANTAGES

Our system stands out in several ways for quick, low-cost health checks in everyday settings:

1. **No Travel Needed:** Skip long clinic queues. Get prediction in seconds on any phone.
2. **Instant Doctor Link:** Pay low cost, open messaging chat with pre-filled symptoms.
3. **Safe Home Tips:** Shows remedies only when confidence high—students in hostels avoid unnecessary trips.
4. **Doctor Dashboard Simple:** Sees only paid patients, replies when free—earns from short chats.
5. **Light Resource Use:** Runs on basic laptop with 8 GB RAM; no heavy servers.
6. **Easy Scaling:** One server handles many users over local network, MySQL keeps all records.
7. **Modular & Open:** Swap model or add features without breaking flow.

7.CONCLUSIONS

This work presents a practical, low-cost health system that turns a simple symptom entry into a full prediction and doctor chat flow. Using Flask for the web server, scikit-learn for the ML model, MySQL for storing profiles and records, and Razorpay for secure payment, the framework runs on any phone browser with modular Python code and separate components like PredictionEngine and ChatLinkGenerator. This design makes it easy to maintain and extend to other areas or features, helping people in rural spots or busy cities check symptoms fast without internet for the main parts.

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