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MediNav: An AI-Driven Specialist Referral Tool to Reduce Wait Times in Indian Public Hospitals

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ABSTRACT

Public hospitals in India face significant challenges with long patient wait times, particularly due to disorganized referral systems. Many patients approaching these hospitals come from underserved backgrounds or have limited health literacy and often struggle to identify the appropriate type of doctor for their specific health issues. As many public hospitals in India lack a structured first point of contact or General Practitioner (GP) system, this confusion contributes to unnecessary delays and increased wait times. To address this issue, the study introduces MediNav, an AI-powered tool designed to evaluate patient symptoms and guide them to the right type of doctor for consultation. By doing so, MediNav enhances patient flow and minimizes unnecessary delays, particularly benefiting those who may not know how to navigate the healthcare system. The AI model, developed using XGBoost on symptom–specialty data, achieved an overall accuracy of 85.58% in live primary healthcare (PHC) settings. Through a comparative assessment of wait times, MediNav has the potential to reduce patient waiting time stemming from misreferrals or department transfers by an average of 39.4 minutes per individual in public Indian hospitals. In the absence of a GP or structured referral layer, such inefficiencies are common in India's public hospitals. With typical patient volumes of 500 or more per day, this translates to over 328 clinical hours saved daily. This significant reduction can enhance clinical efficiency within strained public health systems, ultimately improving access to care for all patients, especially those with limited understanding of the healthcare process.

Keywords: *Patient Triage, Indian Hospital Waiting Time, Symptom-Based Routing*

1.INTRODUCTION

The Indian public healthcare system, particularly in high-density urban centers like Delhi, faces a critical structural bottleneck: overcrowded Outpatient Departments (OPDs) and a lack of formal triage, leading to inefficiencies in patient routing and prolonged wait times. In hospitals like AIIMS Delhi, patients frequently arrive as early as 5:00 a.m. only to wait several hours and be redirected across multiple departments without receiving definitive care. On March 20, 2024, multiple patients reported waiting over four hours in the Orthopaedics queue before being referred to Gastroenterology or Neurology, highlighting the dysfunction in specialist allocation pathways. *This observation is based on field notes and verbal interviews conducted at AIIMS Delhi, March 2024 (unpublished data).*

These delays are not anomalies but symptoms of a systemic absence of a gatekeeping general physician model.

Unlike many countries where general practitioners serve as the primary point of contact, India's public hospitals often lack this layer of triage, forcing patients to self-select departments based on their perceived needs. This not only overwhelms super-specialty units but also causes significant resource misallocation and compromises timely treatment. These issues collectively call for a scalable, intelligent, and clinically sensitive mechanism to streamline initial patient-specialist matching.

Public hospitals currently operate without a structured intake or referral mechanism at the outpatient level. Patients with general symptoms—such as fatigue, chest pain, or headache—may queue for hours in an unrelated department, only to be rerouted, causing cascading delays across departments. Existing appointment portals and hospital apps do not offer medically informed triage support. This inefficiency is particularly burdensome in high-volume tertiary hospitals like Safdarjung, AIIMS, and RML in Delhi, where OPDs receive upwards of 8,000–12,000 walk-ins daily.

Furthermore, patients from lower-income backgrounds or rural regions who travel long distances to urban hospitals are disproportionately affected. The absence of a centralised triage model translates into lost wages, extended hospital congestion, and delayed intervention for critical cases.

Over the past decade, multiple digital health tools have emerged globally to assist patients in identifying potential medical issues based on symptoms.

Tools such as WebMD, Ada Health, and Babylon provide AI-generated suggestions for conditions and sometimes propose whether to seek urgent care. However, these models primarily focus on disease prediction, not department-level routing. They also operate as closed systems trained on Western epidemiological datasets and are rarely validated in the Indian clinical environment. No current AI tools trained on public health datasets in India are designed to **predict the appropriate medical specialty based on symptom input with real-world validation**. Most outpatient routing, even in national-level hospitals, is managed through manual screening desks or crowd-based assumptions. This creates clinical delays, logistical inefficiencies, and inconsistent care pathways.

What differentiates **MediNav** from these existing systems is its use of localized symptom-specialist data, field-tested validation in a Primary Health Centre (PHC), and integration potential with public hospitals. Unlike conventional symptom checkers, MediNav doesn't diagnose diseases; it provides department-level specialist routing: a practical and scalable intervention uniquely suited for India’s overburdened public hospitals.

3. MATERIALS AND METHODS

3.1 Dataset Source and Description

The training dataset for MediNav was obtained from an open-access repository on Kaggle, titled “Disease Prediction Using Machine Learning.” [1] It comprises 4,920 samples and 133 columns, where 132 columns represent binary-encoded symptoms (1 = present, 0 = absent) and the final column indicates a disease prognosis.

For this study, the prognosis column was retained only for initial mapping to a relevant medical specialty. Each disease label was manually assigned to a corresponding clinical department or specialist type based on standard referral practices. The prognosis column was then removed before model training, as MediNav’s objective is not to predict diseases but to recommend the appropriate specialty for referral.

3.2 Data Preprocessing

All symptom features were maintained in binary format, with no missing values in the dataset. The new target label, doctor_specialty, was encoded using LabelEncoder from scikit-learn[3] for compatibility with the XGBoost classifier. Class balance was reviewed, and no resampling was applied, as the symptom-based variance was deemed sufficient to generalize over multiple specialties.

3.3 Model Development

MediNav’s core engine utilizes the XGBoost (Extreme Gradient Boosting) algorithm[2], implemented through xgboost.XGBClassifier. The dataset was split into training and test sets in an 80:20 ratio using train_test_split with a fixed random_state for reproducibility.

The model was trained to perform multiclass classification to predict the doctor_specialty based on the patient’s symptom input. The training did not include disease-specific features or diagnostics. Performance was evaluated using **accuracy score** on the test set, achieving a classification accuracy of **85.58%**.

3.4 Symptom Input Interface (User Interaction Protocol)

MediNav is currently deployed as a Colab-based interface for proof-of-concept testing. Users are presented with a list of available symptoms (based on the dataset’s 132 columns). They input their symptoms as a comma-separated list using underscores for spacing (e.g., chest_pain, fatigue, headache).

A pre-processing script converts this list into a binary input vector matching the model’s feature schema. This input vector is passed to the trained XGBoost model, which returns the predicted medical specialty. This minimal-input format was chosen to simulate a web-app flow and maintain reproducibility in field testing.

```
113. receiving_unsterile_injections
114. coma
115. stomach_bleeding
116. distention_of_abdomen
117. history_of_alcohol_consumption
118. fluid_overload.1
119. blood_in_sputum
120. prominent_veins_on_calf
121. palpitations
122. painful_walking
123. pus_filled_pimples
124. blackheads
125. scurring
126. skin_peeling
127. silver_like_dusting
128. small_dents_in_nails
129. inflammatory_nails
130. blister
131. red_sore_around_nose
132. yellow_crust_ooze
Enter the names of the symptoms you have, separated by commas (e.g., itching, skin_rash): muscle_pain, depression, watering_from_eyes
Predicted doctor specialty: Allergist
```

Fig.1: Example of the prototype working.

3.5 Field Evaluation in Primary Health Centre (PHC)

A field validation study was conducted at **Khemchand Chug Arya Samaj Dispensary**, a Primary Health Centre in New Delhi, under the supervision of **Dr. Sumit Kumar**. A total of **105 patients** presenting with general symptoms were enrolled over a multi-day period.

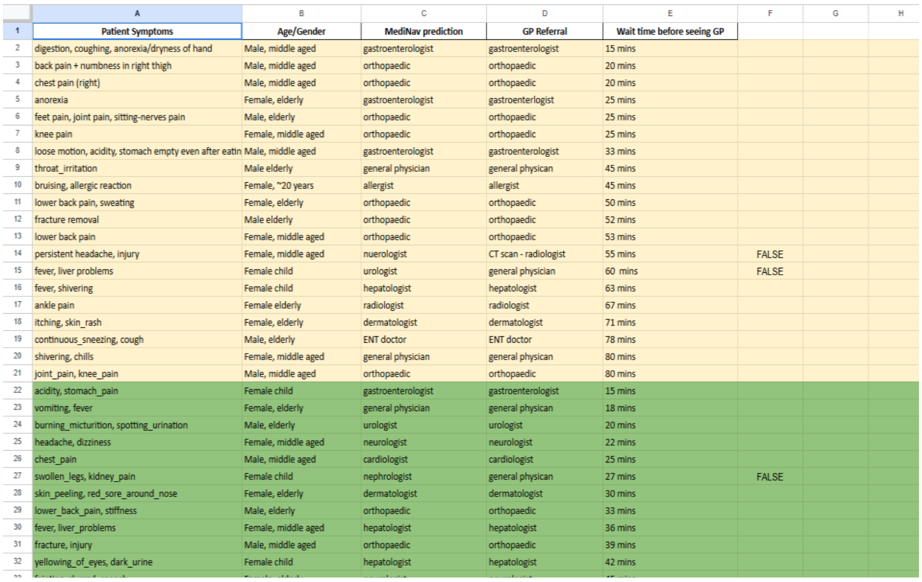
Fig. 2: Example of set-up at PHC where the study was conducted

For each patient, symptoms were recorded and entered into the MediNav system to obtain a predicted specialist department. These predictions were compared with the referral decisions made by the attending physician at the PHC. Cases where the MediNav-predicted department matched the physician's referral were recorded as true positives for routing accuracy. This provided the basis for calculating the real-world performance of the model in a clinical setting.

4. RESULTS

4.1 Model Performance in Clinical Setting

A real-world evaluation of the MediNav model was conducted under the guidance of Dr. Poorvee Mathur, GM Research, Max Healthcare Institute Ltd. on 105 patients at the **Khemchand Chug Arya Samaj Dispensary**, a **Primary Health Centre (PHC) in New Delhi.** Each patient's symptoms were recorded and entered into the MediNav system, which produced a department-level referral recommendation. These outputs were compared with the referrals made by the attending physician, Dr. Sumit Kumar.
Out of 105 patient cases, 90 matched the actual referral decision of the physician. The resulting real-world classification accuracy of the MediNav system was:
Accuracy = 90 / 105 = 0.8571 or 85.71%
This closely aligns with the model's test-set performance accuracy of **85.58%** obtained during offline evaluation on the Kaggle dataset, thus validating the model's generalizability across both synthetic and real-world inputs.



1	Patient Symptoms	Age/Gender	MediNav prediction	GP Referral	Wait time before seeing GP	
2	digestion, coughing, anorexia/dryness of hand	Male, middle aged	gastroenterologist	gastroenterologist	15 mins	
3	back pain + numbness in right thigh	Male, middle aged	orthopaedic	orthopaedic	20 mins	
4	chest pain (right)	Male, middle aged	orthopaedic	orthopaedic	20 mins	
5	anorexia	Female, elderly	gastroenterologist	gastroenterlogist	25 mins	
6	feet pain, joint pain, sitting-nerves pain	Male, elderly	orthopaedic	orthopaedic	25 mins	
7	knee pain	Female, middle aged	orthopaedic	orthopaedic	25 mins	
8	loose motion, acidity, stomach empty even after eatin	Male, middle aged	gastroenterologist	gastroenterologist	33 mins	
9	throat_irritation	Male elderly	general physician	general physican	45 mins	
10	bruising, allergic reaction	Female, ~20 years	allergist	allergist	45 mins	
11	lower back pain, sweating	Female, elderly	orthopaedic	orthopaedic	50 mins	
12	fracture removal	Male elderly	orthopaedic	orthopaedic	52 mins	
13	lower back pain	Female, middle aged	orthopaedic	orthopaedic	53 mins	
14	persistent headache, injury	Female, middle aged	nuerologist	CT scan - radiologist	55 mins	FALSE
15	fever, liver problems	Female child	urologist	general physician	60 mins	FALSE
16	fever, shivering	Female child	hepatologist	hepatologist	63 mins	
17	ankle pain	Female elderly	radiologist	radiologist	67 mins	
18	itching, skin_rash	Female, elderly	dermatologist	dermatologist	71 mins	
19	continuous_sneezing, cough	Male, elderly	ENT doctor	ENT doctor	78 mins	
20	shivering, chills	Female, middle aged	general physician	general physican	80 mins	
21	joint_pain, knee_pain	Male, middle aged	orthopaedic	orthopaedic	80 mins	
22	acidity, stomach_pain	Female child	gastroenterologist	gastroenterologist	15 mins	
23	vomiting, fever	Female, elderly	general physician	general physican	18 mins	
24	burning_micturition, spotting_urination	Male, elderly	urologist	urologist	20 mins	
25	headache, dizziness	Female, middle aged	neurologist	neurologist	22 mins	
26	chest_pain	Male, middle aged	cardiologist	cardiologist	25 mins	
27	swollen_legs, kidney_pain	Female child	nephrologist	general physican	27 mins	FALSE
28	skin_peeling, red_sore_around_nose	Female, elderly	dermatologist	dermatologist	30 mins	
29	lower_back_pain, stiffness	Male, elderly	orthopaedic	orthopaedic	33 mins	
30	fever, liver_problems	Female, middle aged	hepatologist	hepatologist	36 mins	
31	fracture, injury	Male, middle aged	orthopaedic	orthopaedic	39 mins	
32	yellowing_of_eyes, dark_urine	Female child	hepatologist	hepatologist	42 mins	

Fig. 3 - Spreadsheet of how sample study was conducted

4.2 Wait Time Measurement and Estimated Time Saved

The mean wait time before seeing a general physician was recorded for all 105 patients during the PHC study. Based on direct observational tracking, the average wait time was **44.16 minutes**. In cases where patients were initially misrouted or queued in an inappropriate department, an additional delay was introduced due to interdepartmental referrals or repeated waiting.
Through retrospective analysis of these cases and patient flow mapping, MediNav was estimated to reduce the average redundant wait time by **39.4 minutes per individual**. This value represents the time saved through a correct first-attempt referral to the appropriate department.

4.3 Extrapolated System-Level Impact

To estimate the scalability of MediNav in high-volume public hospitals, the average time saving of 39.4 minutes per patient was applied to a projected volume of 500 outpatients per day[4]:

Estimated Time Saved Daily = 500 × 39.4 = 19,700 minutes = 19,700 / 60 = **328.33 clinician hours per day**

This operational gain has the potential to significantly reduce congestion in overburdened outpatient departments, especially in tertiary hospitals serving large urban populations.

5. CONCLUSION

In conclusion, the introduction of MediNav as an AI-based specialist referral system represents a significant advancement in addressing the persistent issue of long wait times in Indian public hospitals. By leveraging machine learning algorithms, specifically XGBoost, MediNav effectively evaluates patient symptoms and directs them to the appropriate medical specialty, thereby streamlining the referral process. The study highlights the critical structural challenges faced by the Indian public healthcare system, particularly in urban centers where overcrowding and disorganized patient routing are prevalent. The lack of a formal triage system exacerbates these issues, especially for patients from underserved backgrounds who may struggle to navigate the complexities of healthcare access. The empirical results demonstrate that MediNav not only matches the referral decisions made by healthcare professionals with high accuracy but also has the potential to significantly reduce patient wait times. By saving an average of 39.4 minutes per patient and potentially freeing up over 328 clinical hours daily in high-volume hospitals, MediNav offers a scalable solution to improve clinical efficiency and enhance patient care in India's overburdened healthcare landscape. This innovative approach not only optimizes resource allocation but also fosters equitable access to timely medical attention, particularly for vulnerable populations, thereby addressing a critical gap in the current healthcare delivery model.

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