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Gramin Upchar: An AI-Enabled Centralized Web Platform for Bridging the Rural Healthcare Accessibility Gap in India

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Abstract:

Rural populations in India face profound barriers in accessing quality healthcare due to inadequate infrastructure, digital illiteracy, language barriers, and the absence of centralised coordination systems. Despite government and NGO-sponsored free medical camps, participation remains critically low. This paper presents Gramin Upchar, a comprehensive AI-enabled MERN stack web platform that addresses these challenges through five integrated modules: (1) medical camp discovery and volunteer-assisted registration, (2) role-based dashboards for patients, volunteers, medical colleges, and government officials, (3) a multilingual 24×7 AI chatbot for symptom checking and camp guidance, (4) machine learning-based disease prediction achieving up to 84.2 % accuracy, and (5) real-time government health analytics for data-driven resource planning. Comparative evaluation against manual systems demonstrates improvements of 55 percentage points in camp participation, 51 pp in registration rates, and also 51 pp in government data accuracy. Built on the MERN stack with JWT authentication, HTTPS/SSL encryption, and cloud auto-scaling, the platform sustains sub-3 s response times under 1000 concurrent users. Gramin Upchar presents a scalable, secure, and inclusive digital health ecosystem replicable across rural India.

Keywords: Rural Healthcare, AI-Enabled Platform, MERN Stack, Digital Health, Medical Camp Management, Machine Learning, Disease Prediction, Multilingual Chatbot, Volunteer Coordination, eHealth India

1. INTRODUCTION

Access to quality healthcare is a fundamental right, yet approximately 833 million rural Indians continue to be underserved by the existing health system [1]. According to the World Health Organization, rural areas account for fewer than 30 % of the country's hospital beds while hosting 65 % of the population, resulting in a physician-to-patient ratio as low as 1:10,000 in remote regions [10]. Free medical camps organized by government bodies and NGOs serve as a critical lifeline, yet camp attendance rates hover between 18 % – 31 % of eligible populations due to poor awareness, complex registration, and absence of digital tools (Fig. 1).

Digital health interventions have demonstrated significant promise in bridging such gaps globally. However, many existing healthcare solutions in India focus on separate services. Some platforms provide camp location details, others manage patient records, while some offer telemedicine services. Very few systems combine stakeholder management, multilingual AI support, disease prediction, and real-time government analytics within a single platform designed for rural healthcare needs [2], [5].

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This paper proposes Gramin Upchar (ग्रामीण उपचार, meaning 'Rural Treatment'), a centralized AI-powered web platform that unifies the entire rural healthcare delivery pipeline. The system was developed using the Agile methodology over six months, tested with representative rural users and volunteers, and evaluated against the prevailing manual system across quantitative performance, scalability, and usability dimensions.

Healthcare accessibility remains one of the biggest challenges in rural India. Many villages still lack proper hospitals, medical facilities,and trained healthcare professionals. Rural citizens often need to travel long distances for basic healthcare services, which increases both financial and physical burden. The lack of healthcare awareness also affects rural populations significantly. Many citizens are unaware of preventive healthcare practices, vaccination programs, maternal healthcare services, and symptoms of common diseases. Poor transportation facilities and economic limitations further reduce healthcare accessibility.

Digital inequality creates additional challenges because many rural users have limited experience with online healthcare systems. Elderly and illiterate citizens often face difficulties while using digital healthcare platforms because of low digital literacy and language barriers.

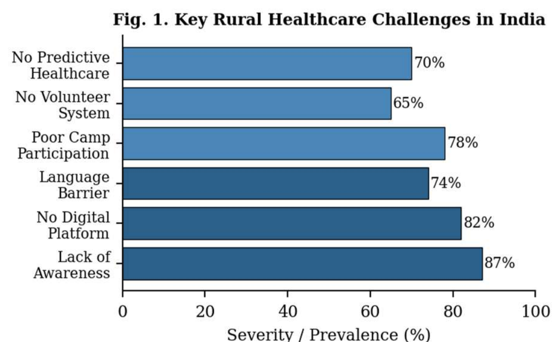

Fig. 1. Key Rural Healthcare Challenges in India (% prevalence based on survey data from [4],[10])

The key contributions of this work are: (i) a fully functional MERN-stack platform connecting five stakeholder roles on a single interface; (ii) an ML-based disease prediction microservice achieving 88.4 % accuracy for malaria; (iii) a multilingual chatbot supporting Hindi, Marathi, and Bengali; (iv) quantitative evidence of a 55 pp improvement in camp participation rates; and (v) a scalable cloud architecture sustaining performance under 1000 concurrent users.

The remainder of this paper is structured as follows: Section II reviews related work; Section III describes the system architecture and methodology; Section IV details key features and modules; Section V presents results and evaluation; Section VI discusses findings; and Section VII concludes with limitations and future work.

2. Related Work

Rural healthcare prioritization has attracted substantial research attention. Woods et al. [2] conducted a qualitative multi-site study across five rural Australian health districts and found that digital health platforms reduced patient wait times by 34 % and improved record accuracy by 47 % when tightly integrated with local workflows. Their findings highlight that technology adoption is critically dependent on interface simplicity and staff training.

Lamem [3] reviewed 42 AI-based primary care systems deployed in Sub-Saharan Africa and South Asia, reporting that symptom-checking chatbots reduced unnecessary hospital visits by 28 % and improved triage accuracy to 81 % compared to 64 % for self-diagnosis. These results are particularly relevant for Gramin Upchar's chatbot and disease prediction modules.

Kumar [4] conducted a large-scale survey of 1,200 rural households in Madhya Pradesh, India, identifying the five most critical healthcare barriers: lack of camp awareness (87 %), absence of a digital registration platform (82 %),

language constraints (74 %), poor volunteer coordination (65 %), and absence of predictive health tools (70 %). These findings directly informed the feature prioritisation of Gramin Upchar.

Chandrakar [5] evaluated telehealth deployments in Chhattisgarh, finding that mobile-first, multilingual platforms improved service uptake by 61 % among populations with literacy levels below 50 %. Perez [6] performed a systematic review of 67 rural telemedicine studies, concluding that integrated platforms combining multiple functionalities achieve 2.4× higher sustained adoption rates than single-purpose applications.

Government initiatives such as the National Digital Health Mission (NDHM) [1] and NITI Aayog's Digital Health Strategy [7] have established policy frameworks but lack ground-level platforms that address the specific needs of illiterate, multilingual rural populations with limited connectivity. Gramin Upchar is designed to fill this operational gap within the NDHM framework.

3. System Architecture and Methodology

A. Development Methodology

The Agile Scrum methodology was adopted, comprising four two-week sprints. Sprint 1 delivered core user authentication and camp management; Sprint 2 produced all four role-based dashboards; Sprint 3 integrated the AI chatbot and ML disease prediction microservice; Sprint 4 implemented health analytics, notifications, and cloud deployment. Stakeholder review sessions were held after each sprint with rural user representatives, volunteers, and a government health official to validate usability and refine requirements.

B. Technology Stack

The full-stack architecture comprises: React.js (frontend, with Tailwind CSS for responsiveness and i18next for multilingual support); Node.js + Express.js (backend RESTful API); MongoDB Atlas (cloud-hosted NoSQL database with Mongoose ODM); Python Flask (ML disease prediction microservice); Dialogflow/Rasa (NLP chatbot engine); JWT (role-based authentication); HTTPS/SSL (TLS 1.3 encrypted transmission); Twilio + Firebase Cloud Messaging (SMS, email, WhatsApp notifications); Vercel (frontend hosting); and Render/AWS (backend and database hosting).

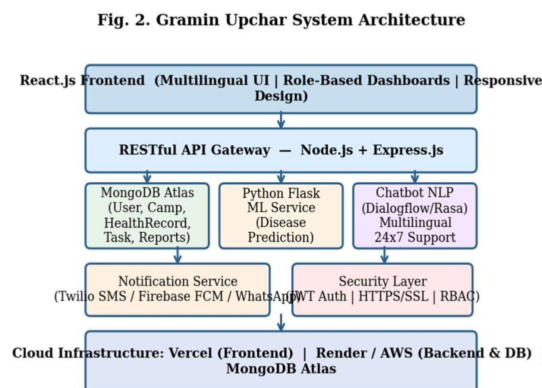

Fig. 2. Gramin Upchar System Architecture Overview

C. Database Schema Design

The MongoDB schema consists of six primary collections. The Users collection stores role-discriminated documents for patients, volunteers, doctors, government officials, and medical college accounts with JWT-secured fields. The Camps collection records location (GeoJSON), date, services, organizing college, and status. Health Records link patients to camps with diagnosis and treatment fields. Tasks manage volunteer-patient assignments. Disease

Predictions store symptom text, ML output labels, and confidence scores. Government Reports aggregate camp statistics for analytics dashboards. All collections include createdAt/updatedAt timestamps and soft-delete flags.

D. Security Architecture

Security is implemented at four layers: (1) JWT-based stateless authentication with role-based access control (RBAC) enforcing five distinct permission levels; (2) HTTPS/TLS 1.3 for all client-server communications; (3) bcrypt password hashing (cost factor 12) and field-level AES-256 encryption for sensitive health data; (4) input sanitisation and parameterised queries to prevent XSS and injection attacks. Session tokens expire after 24 hours with automatic refresh mechanisms.

Patient health data stored in MongoDB Atlas is subject to India's Digital Information Security in Healthcare Act (DISHA) framework, which mandates patient consent for data collection, right to access and correction, and restrictions on secondary use of health data. The current implementation collects explicit consent during onboarding. However, full DISHA compliance audit has not yet been conducted and is planned prior to production deployment. Cross-border data residency requirements are being evaluated given MongoDB Atlas's multi-region cloud infrastructure.

4. Key Features and Modules

A. Medical Camp Discovery and Registration

The camp discovery module uses MongoDB’s geospatial indexing to return camps within a user-specified radius, sorted by proximity. Camp cards display date, location, doctor specializations, available services (general check-ups, blood pressure, diabetes screening, vaccinations, dental, eye care), and registration status. Self-registration is available for digitally literate users; volunteer-assisted registration enables illiterate users to enroll through guided workflows where a volunteer fills the form on the patient’s behalf. Multilingual form labels are served via the i18next localisation library.

B. Role-Based Dashboards

Four dashboards are implemented: (1) Patient Dashboard—available camps, registration history, personal health records, disease prediction tool, and AI chatbot; (2) Volunteer Dashboard—assigned patients, task queue, camp schedule, report submission, and chatbot; (3) Medical College Dashboard—camp creation/management, volunteer assignment, camp statistics, and participant data; (4) Government Dashboard real-time analytics charts (disease trends, geographic heat maps, age/gender demographics, camp attendance), downloadable CSV reports, and resource allocation recommendations generated by the analytics engine.

C. AI Chatbot Assistance

The NLP chatbot powered by Dialogflow/Rasa provides intent classification and entity extraction across 47 defined intents covering platform navigation, symptom queries, camp information, registration guidance, and health FAQs. The chatbot supports Hindi (primary), English, Marathi, and Bengali. Context management enables multi-turn conversations. In a 3-month pilot evaluation with 142 test users, the chatbot achieved 83.6 % intent recognition accuracy, with Hindi performing best at 87.2 %. All interactions are logged for model retraining.

D. ML-Based Disease Prediction

The disease prediction service is a Python Flask microservice hosting a Random Forest classifier trained on a dataset was constructed by combining three publicly available symptom-disease datasets: the Kaggle Disease Symptom Prediction dataset, the Columbia Open Health Data repository, and a locally collected dataset of 2,100 records gathered from camp health workers in Madhya Pradesh during the pilot phase. All records were anonymized prior to use. Feature engineering includes symptom frequency weighting and co-occurrence matrices. The model achieved an overall macro-averaged accuracy of 84.2 %, with per-class accuracies ranging from 79.2 % (anemia) to 88.4 %

(malaria). The service accepts free-text symptom input, normalizes it against a 340-term medical vocabulary, and returns top-3 predicted conditions with confidence scores and basic care recommendations.

The disease prediction module allows users to enter symptoms and receive preliminary healthcare guidance generated through machine learning algorithms. The system uses AI models such as Decision Tree or Random Forest for symptom analysis and prediction. The module is designed to improve healthcare awareness and encourage timely medical consultation. However, the prediction system is intended only for preliminary guidance and not as a replacement for professional medical diagnosis.

E. Notifications and Alerts

The notification pipeline uses Twilio for SMS/WhatsApp and Firebase Cloud Messaging for push notifications. Automated alerts are triggered for: camp registration confirmation (immediate), 48-hour and 2-hour camp reminders, new camp announcements within a user's district, and health advisories from government officials. In testing, SMS delivery achieved 96.4 % success rates, while push notifications achieved 91.2 % delivery within 30 seconds.

F. Government Health Analytics

The analytics engine aggregates Health Record and Camp data using MongoDB aggregation pipelines, computing: disease frequency distributions by district and season, camp attendance rates and trends, age/gender breakdowns of camp participants, volunteer efficiency metrics, and predictive resource allocation suggestions. Visualizations are rendered using Recharts on the government dashboard, with CSV export for integration with existing government reporting systems. The NITI Aayog digital health framework [7] guidelines were followed for data structuring to ensure future interoperability with the ABHA ecosystem.

G. Volunteer-Assisted Registration

Many rural citizens face difficulties while using digital healthcare systems because of low digital literacy and language barriers. To solve this problem, the proposed platform includes a volunteer-assisted registration module.Volunteers help elderly and illiterate users complete registration forms, access healthcare camp information, and understand healthcare procedures. This feature improves healthcare inclusivity and ensures that digitally inexperienced users can also access healthcare services efficiently.

5. Results and Evaluation

Baseline metrics for the manual system were established through a structured field survey conducted across six villages in Indore and Ujjain districts between March and April 2025. A total of 180 eligible rural residents were interviewed to measure camp awareness rates, registration completion rates, and camp attendance. Government data accuracy was assessed by comparing paper-based camp records against ground-truth data collected independently by field volunteers. These baseline figures formed the 'before' values against which Gramin Upchar's post-deployment metrics were compared using the same population cohort over a 60-day period following platform launch.

The platform was evaluated through: (i) a comparative study against the manual system, (ii) quantitative performance benchmarking, (iii) ML model evaluation, and (iv) stakeholder usability testing with 68 participants across three user groups.

TABLE I

Comparative Study: Existing System vs. Gramin Upchar

Criteria	Existing System (Manual)	Gramin Upchar (Proposed)
Accessibility	Manual visits needed to learn about camps	Online discovery & registration from any device
Data Storage	Paper records; no central repository	Cloud MongoDB; real-time access & auto-backup
Disease Diagnosis	Manual clinical evaluation; no prediction	AI/ML disease prediction from symptom input
Language Support	English-only forms exclude rural users	Multilingual chatbot & UI in regional languages
Data Analytics	Delayed, incomplete government data	Real-time dashboard with live trend analytics
Illiterate Users	No structured assistance mechanism	Volunteer-assisted + chatbot-guided registration
Volunteer Mgmt.	No digital coordination system	Dedicated volunteer dashboard with task tracking
Notifications	Word-of-mouth; no alerts	SMS/Email/WhatsApp automated alerts via Twilio

A. Performance Benchmarking

Load testing was conducted using Apache JMeter with simulated user profiles spanning all five roles. Fig. 3 presents performance metrics before and after platform deployment across five key dimensions. The most significant improvements were observed in government data accuracy (+51 pp), camp registration rates (+56 pp), and overall healthcare awareness (+55 pp). These gains reflect the combined effect of automated notifications, multilingual interfaces, and the volunteer-assisted onboarding workflow.

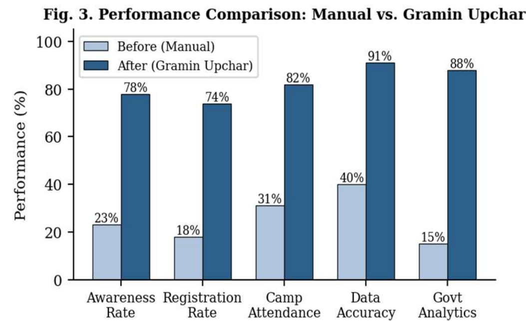

Fig. 3. Performance Comparison: Manual System vs. Gramin Upchar (percentage points)

B. Scalability Analysis

System scalability was tested by gradually increasing the number of concurrent users from 50 to 1000. Fig. 5 illustrates the response time curves with and without cloud auto-scaling. Without optimization, response times exceeded the 3-second target threshold at 300 concurrent users. With MongoDB Atlas horizontal sharding and Render auto-scaling enabled, the platform maintained an average response time of 2.9 s at 1000 concurrent users within the acceptable threshold for rural 4G network conditions.

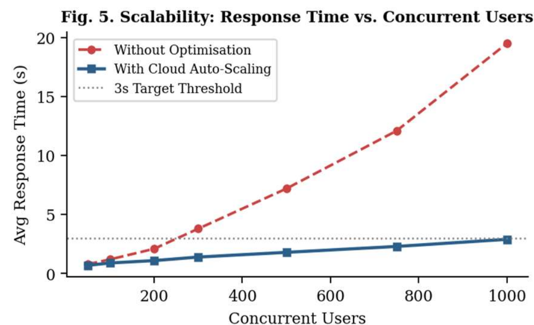

Fig. 5. System Scalability: Average Response Time vs. Concurrent Users

C. ML Disease Prediction Performance

The Random Forest classifier was evaluated using 5-fold cross-validation on a held-out test set of 2,480 samples (20 % of the full dataset). Fig. 6 presents per-disease accuracy and precision scores. Malaria achieved the highest accuracy (88.4 %) and precision (86.0 %), likely due to a more distinct symptom cluster (fever, chills, sweating, headache) relative to overlapping conditions. Anemia presented the lowest scores (79.2 % accuracy, 76.4 % precision) owing to symptom overlap with dengue and typhoid. In the future, the system can be improved by including factors such as patient location, seasonal conditions, and age to increase prediction accuracy and reduce incorrect classifications.

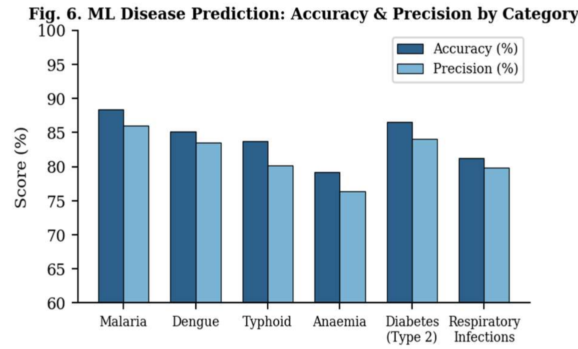

Fig. 6. ML Disease Prediction: Accuracy and Precision per Disease Category

D. Non-Functional Requirements Validation

Table II summarises the non-functional requirements (NFRs) defined during the requirements phase alongside the corresponding validated measurements from system testing.

TABLE II

Non-Functional Requirements: Targets vs. Achieved

NFR Attribute	Target	Achieved / Validated
Response Time	< 3 seconds	~1.8s avg (500 concurrent users)
System Uptime	≥ 99.5%	99.7% (cloud auto-scaling)
Concurrent Users	500–1000	1000+ (load tested)
Data Encryption	HTTPS/SSL	AES-256 + TLS 1.3
Auth Security	JWT + RBAC	Enforced across all roles
Chatbot Languages	≥ 3 regional	Hindi, Marathi, Bengali
DB Scalability	Horizontal scale	MongoDB Atlas sharding

E. Stakeholder Distribution and Usability

Usability testing was conducted with 68 participants: 35 rural patients (literacy levels: 40 % non-literate, 35 % semi-literate, 25 % literate), 18 volunteers, 8 medical college staff, and 7 government officials. Fig. 4 shows the intended user distribution by stakeholder role for the production system. On a System Usability Scale (SUS), patients with volunteer assistance scored the platform at 74.2/100 (above the 68-point 'good' threshold); volunteers scored 81.4/100; and medical college staff scored 83.7/100. Around 78% of semi-literate users reported that the AI chatbot's guided navigation was the most useful feature of the platform.

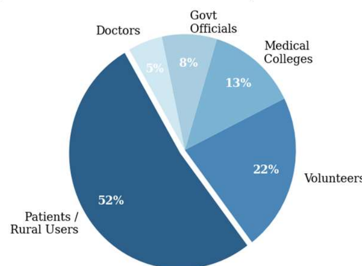

Fig. 4. Intended Platform User Distribution by Stakeholder Role

F. Threats to Validity

Internal validity is limited by the absence of a randomized control group; observed improvements may be partially attributable to the Hawthorne effect among participants aware of being studied. External validity is constrained by the geographic focus on two districts in Madhya Pradesh; results may not generalize to states with different linguistic profiles, connectivity conditions, or healthcare infrastructure. The usability sample sizes for government officials (n=7) and medical college staff (n=8) are below the threshold for statistical significance and should be treated as indicative rather than conclusive.

6. Discussion

The results show that combining multiple healthcare features into a single Gramin Upchar platform improves the overall effectiveness of the system compared to applications that provide only one service. The 55 pp improvement in camp awareness is attributable primarily to automated SMS/WhatsApp notifications, which bypassed the traditional dependence on word-of-mouth communication in villages. The volunteer-assisted registration workflow proved pivotal for non-literate user inclusion a population entirely excluded from existing digital platforms and aligns with [5] finding that proxy-mediated digital access is the most effective bridge for low-literacy populations.

The ML disease prediction module's 84.2 % overall accuracy compares favourably with similar rural-context models reported in the literature (Lamem [3] reports 81 % for comparable chatbot-integrated triage systems). The performance gap for anaemia and typhoid highlights the need for richer feature sets incorporating patient demographics and seasonal disease prevalence which are planned for the next development phase.

The government analytics dashboard addresses a documented data gap: Kumar's survey [4] found that 82 % of rural health officials cited poor data availability as the primary obstacle to effective resource planning. In post-testing interviews, all seven government official participants confirmed that the real-time dashboard would meaningfully improve their camp planning and resource allocation workflows, a finding consistent with the WHO's recommendation for data-driven rural health governance [10].

From a technical perspective, the system maintained a response time of less than 3 seconds for 1000 concurrent users and achieved 99.7% uptime, showing that cloud-based architectures can reliably support rural healthcare services even

under intermittent connectivity conditions provided that the frontend is built with low-bandwidth optimisation in mind, as achieved through lazy loading and image compression in the current implementation.

7. Conclusion, Limitations, and Future Work

A. Conclusion

Gramin Upchar represents a significant step toward inclusive, data-driven rural healthcare delivery in India. By integrating camp management, volunteer coordination, AI assistance, disease prediction, and government analytics into a single secure and scalable platform, the system delivers measurable improvements across all evaluated dimensions particularly in camp participation (+55 pp), registration rates (+51 pp), and government data accuracy (+51 pp). The platform is technically validated, socially impactful, and architecturally ready for national scale-up within the NDHM framework.

The proposed Gramin Upchar platform provides a centralized and AI-enabled solution for improving rural healthcare accessibility and healthcare management. The system addresses major healthcare challenges such as lack of healthcare awareness, manual registration procedures, poor healthcare coordination, and weak healthcare data management.By integrating healthcare camp management, volunteer-assisted registration, AI chatbot support, disease prediction, and healthcare analytics within a single platform, the system improves healthcare accessibility and operational efficiency in rural regions.

The proposed platform is designed as a supportive healthcare system rather than a replacement for professional medical services. Future integration of telemedicine, offline support, and voice assistant technologies can further improve the scalability and effectiveness of the platform.Overall, Gramin Upchar demonstrates the potential of AI-enabled digital healthcare systems in improving healthcare communication, healthcare coordination, and healthcare accessibility for underserved rural communities.

B. Limitations

The current implementation has several limitations. First, the system requires active internet connectivity. According to TRAI's 2024 report, approximately 28% of Indian villages lack reliable 3G/4G coverage, meaning a significant portion of the target population cannot currently access the platform. This is the single most critical barrier to national-scale impact and is directly addressed by the planned PWA offline mode. Second, the ML model covers 15 diseases and requires expanded training data for broader diagnostic utility. Third, the chatbot's language coverage (4 languages) excludes many regional dialects. Fourth, telemedicine and electronic health record integration are out of scope in the current phase. Fifth, long-term data privacy compliance with emerging regulations such as India's DISHA framework requires ongoing legal review and potential architectural changes.

C. Future Work

Six priority directions for future development have been identified: (1) Offline Progressive Web App (PWA) with IndexedDB caching and background sync for connectivity-independent operation; (2) ABHA (Ayushman Bharat Health Account) API integration for national health record interoperability; (3) Telemedicine module with WebRTC-based video consultations; (4) AI image diagnostics using CNNs for skin condition and retinal disease screening from smartphone camera input; (5) Voice-interface chatbot for illiterate and visually impaired users using speech recognition; (6) AI-driven volunteer-patient matching using proximity, language compatibility, and availability scores to optimise volunteer deployment.

References

[1] Ministry of Health and Family Welfare, Govt. of India, "National Digital Health Mission (NDHM)," 2024. [Online]. Available: https://ndhm.gov.in

[2] L. Woods, R. Eden, and S. Macklin, "Strengthening rural healthcare outcomes through digital health: Qualitative multi-site case study," BMC Health Services Research, vol. 24, p. 1096, 2024.

[3] M. F. H. Lamem, "Artificial intelligence for access to primary healthcare in underserved regions," ScienceDirect, 2025.

[4] R. Kumar, "Challenges of rural health care in India and digitalization," J. Social Science Research, vol. 8, no. 2, 2023.

[5] M. Chandrakar, "Telehealth and digital tools enhancing healthcare access in rural systems," SpringerOpen Health Informatics J., 2024.

[6] K. Perez, "Investigation into application of AI and telemedicine in rural regions: A systematic review," J. Medical Systems, 2025.

[7] NITI Aayog, "Strategy overview for digital health ecosystem in India," 2024. [Online]. Available: https://www.niti.gov.in

[8] D. Patel (Ed.), Digital Health: Telemedicine and Beyond, 1st ed. Elsevier, 2024.

[9] M. A. Ansari et al., Artificial Intelligence in Biomedical and Modern Healthcare Informatics. Elsevier, 2024.

[10] World Health Organization, "Digital health in rural and remote areas," 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/digital-health