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Application for Enlightening the People about Government Schemes Regarding Health

Mrs. A. Getsyal[1], T. Sathya Narayana[2], M. Sheik Mohamed[3], R. Sarath Kumar[4], V. Sarva Sathiyan[5]
[1]*M.E., Assistant Professor, Dept. of CSE, MIET Engineering College, Tiruchirappalli, India*
[2, 3, 4, 5]*Dept. of Computer Science and Engineering, MIET Engineering College, Tiruchirappalli, India*

Abstract: ***Millions of citizens across India are unable to access government health schemes due to lack of awareness, complex eligibility criteria, and inadequate information dissemination. Traditional healthcare portals are inadequate in providing personalised scheme recommendations and early disease risk predictions. This paper presents Accessible Assist, a web-based platform designed to bridge the gap between citizens and government health and welfare schemes, aligned with SDG Goal 3: Good Health and Well-being. The system implements a multi-feature architecture centred on three pillars: (i) a personalised scheme eligibility engine that recommends relevant central and state government health schemes from a curated database covering 10+ schemes; (ii) an AI-powered health risk prediction module that collects basic health parameters and predicts early risk for 6+ diseases including diabetes, hypertension, and anaemia; and (iii) a conversational AI chatbot capable of answering user queries in natural language. Evaluation on functional test cases demonstrates precision and recall above 0.85 across all predictive modules. The platform features a responsive teal-green design built with React and Vite, and demonstrates a scalable, citizen-centric solution suitable for deployment across urban and rural India.***

Index Terms: Disease Prediction, Government Scheme Recommendation, Healthcare Accessibility, Machine Learning, Chatbot, SDG Goal 3, React, Web Application.

I. INTRODUCTION

Healthcare accessibility remains a critical challenge in developing regions where awareness of medical resources and government welfare programmes is uneven. Despite the Indian government's commitment to health equity through schemes such as Pradhan Mantri Jan Arogya Yojana (PMJAY), Ayushman Bharat, and various state-level programmes, a significant proportion of eligible citizens fail to access these entitlements. Estimates suggest that between 30 and 60 percent of eligible beneficiaries do not claim their entitled government healthcare benefits, primarily due to inadequate awareness and complexity of eligibility verification processes. Simultaneously, delayed or missed early diagnosis of preventable conditions such as diabetes, hypertension, and anaemia continues to exert a significant burden on the healthcare system. Rural populations and economically weaker sections are disproportionately affected, lacking access to both preventive health guidance and information about financial support mechanisms.

This paper describes Accessible Assist, a web-based platform that integrates AI-powered disease risk prediction with a personalised government health scheme recommendation engine and a conversational chatbot assistant. The system targets citizens with limited digital literacy and provides actionable guidance through a single, accessible interface without requiring prior medical or technical knowledge. The primary contributions of this work are: (i) a unified platform combining disease prediction, scheme recommendation, and chatbot assistance; (ii) a rule-based personalised eligibility engine covering 10+ government schemes; (iii) an AI health risk prediction module covering 6+ disease categories; and (iv) a quantitative evaluation of predictive accuracy and system performance across all core modules.

II. RELATED WORK

A. Disease Prediction Systems

Machine learning approaches to disease prediction have demonstrated strong performance across a range of clinical and community health contexts. Decision Trees, Naïve Bayes, Support Vector Machines, and Random Forest classifiers have been applied extensively to symptom-based datasets to predict conditions including diabetes, cardiovascular disease, and respiratory illness [1][3]. Web-based diagnostic systems using classification techniques enable early intervention by allowing users to input symptoms and receive probabilistic risk assessments [7]. However, the majority of reviewed systems operate in isolation without integration into broader healthcare support or welfare discovery services.

B. Healthcare Recommender Systems

Healthcare recommender systems have been categorised into collaborative filtering, content-based, knowledge-based, and hybrid approaches [2]. These systems assist patients and clinicians in navigating large volumes of medical information by surfacing relevant treatments, medications, or services. Adomavicius and Tuzhilin [1] established a foundational taxonomy for recommender architectures that remains widely referenced. A consistent finding across the literature is that personalisation—tailoring recommendations to individual profiles—substantially improves perceived relevance and uptake [4].

C. AI in Healthcare

Jiang et al. [6] provided a comprehensive survey of artificial intelligence applications across clinical diagnosis, drug discovery, and patient monitoring, confirming the transformative role of AI in healthcare delivery. Islam et al. [7] reviewed machine learning and deep learning techniques for healthcare data analytics, reporting that ensemble and deep architectures consistently outperform single-model baselines on heterogeneous health data. Sarker et al. [8] further documented the growing applicability of AI to preventive care and public health decision support.

D. Identified Research Gap

Across the reviewed literature, three consistent limitations emerge: disease prediction and scheme recommendation are treated as independent problems; government health schemes are not integrated into digital health platforms accessible to lay users; and existing systems do not address the combined accessibility challenges of rural and underprivileged populations. Accessible Assist directly addresses these gaps through a unified, free-access platform.

III. SYSTEM REQUIREMENTS

A. Functional Requirements

The platform must allow users to input basic demographic information (age, income category, state, health category) and receive personalised recommendations for eligible government schemes. Users must be able to input clinical parameters (blood pressure, glucose, BMI, haemoglobin, and related values) and receive risk assessments for six disease categories. A conversational chatbot must respond to user queries in natural language across topics including scheme eligibility, application procedures, and health conditions. An AI-powered report analyser must parse uploaded medical reports and extract actionable health insights.

B. Non-Functional Requirements

All interactive modules must produce responses within 600 ms under standard single-user conditions. The frontend must be responsive across desktop and mobile browsers. The system must validate and sanitise all user inputs to prevent injection attacks and ensure data integrity. The interface must be usable by individuals with low digital literacy, requiring no prior technical knowledge.

C. Hardware and Software Requirements

The recommended deployment configuration specifies an Intel Core i5 or higher processor, 8 GB RAM, and 256 GB SSD storage. The software stack comprises React 18 with Vite for the frontend, Node.js or Python as the backend runtime, MySQL or SQLite for data persistence, and scikit-learn or equivalent for machine learning inference. Security components include AES for data-at-rest encryption, SSL/TLS for transport security, SHA-256 for password hashing, and JWT for session management.

IV. SYSTEM ARCHITECTURE

A. *Architectural Overview*

Accessible Assist follows a client-server architecture with three layers: a React/Vite single-page application frontend, a backend API server handling business logic and ML inference, and a relational database storing scheme metadata, disease rules, and user session data. The general request flow is:

User → React Frontend → REST API → ML/Rule Engine → Database → API → Frontend

The frontend communicates exclusively through REST API endpoints. No sensitive computation occurs client-side. The ML prediction modules are loaded server-side and invoked synchronously on user submission.

B. Disease Prediction Module

The disease prediction module accepts user-supplied clinical parameters as a structured JSON payload. The backend validates the input, normalises numerical features to the training distribution, and passes the feature vector to a pre-trained classifier. The system supports prediction across six disease categories: diabetes, hypertension, anaemia, cardiovascular risk, respiratory conditions, and nutritional deficiency. Rule-based post-processing enriches probabilistic outputs with plain-language risk descriptions and recommended actions.

C. Scheme Recommendation Engine

The recommendation engine evaluates user profile attributes—age, income group, health category, gender, and state—against a curated eligibility rule set for 10+ central and state government health schemes including PMJAY, Ayushman Bharat, JSSK, and related programmes. Matching is performed through a deterministic rule evaluation pipeline that scores each scheme against the user profile and returns ranked recommendations with scheme descriptions, eligibility summaries, and application guidance.

D. Conversational Chatbot

The chatbot module provides natural language interaction for users seeking information about schemes, eligibility, and health topics. It integrates an NLP backend that maps user queries to intent categories and retrieves relevant responses from a structured knowledge base. For queries outside the knowledge base scope, the chatbot acknowledges uncertainty and directs users to authoritative sources.

E. Security Architecture

All data in transit is protected through SSL/TLS. User passwords are stored as SHA-256 hashes with salting. Session management uses JWT with configurable expiry. Sensitive personal health data stored in the database is encrypted using AES-256. All user inputs are validated server-side and sanitised against SQL injection and XSS attack vectors. Role-based access control enforces separation between standard user and administrator functionality.

V. IMPLEMENTATION

A. Frontend

The frontend is implemented in React 18 with Vite as the build tool, delivering fast hot-module replacement during development and optimised production bundles. The interface is structured across four primary modules: Home, Schemes, Eligibility Check, and Health Check (disease prediction and report analysis). A teal-green design aesthetic using CSS custom properties ensures visual consistency. Framer Motion provides animation for bento-grid card transitions. Font Awesome and Google Fonts supply iconography and typography.

B. Backend

The backend exposes a RESTful API handling authentication, scheme eligibility evaluation, disease prediction inference, and chatbot query resolution. Machine learning models are serialised using scikit-learn's joblib persistence format and loaded into memory at server startup to minimise inference latency. Input validation middleware rejects malformed or out-of-range parameters before reaching the model inference layer. Database interactions use parameterised queries to eliminate injection vulnerabilities.

C. Database

The relational database stores scheme metadata (name, eligibility criteria, application links, descriptions), disease parameter reference ranges, and user account records. Scheme data is structured to support efficient rule evaluation without requiring full-table scans. User health inputs are not persisted beyond the active session to minimise privacy risk in the initial deployment.

VI. EXPERIMENTAL EVALUATION

A. Evaluation Methodology

Functional evaluation was conducted using structured test cases covering normal, boundary, and invalid input scenarios for each module. Predictive performance metrics (precision, recall, F1-score) were computed on a held-out test set of 200 labelled instances for the disease prediction module and 150 eligibility cases for the scheme recommendation module. Response latency was measured under single-user conditions on standard development hardware.

B. Module Performance

Table I summarises accuracy, response time, and key outcomes for each core platform module.

TABLE I
Module Performance Summary

Module	Technology	Accuracy	Response	Outcome
Disease Prediction	ML / Rule-Based	87.4 %	< 400 ms	Early risk detection
Scheme Recommendation	Rule Engine	91.2 %	< 300 ms	Personalised schemes
Symptom Input	React + Validation	—	< 100 ms	Clean data pipeline
Chatbot Assistant	NLP / API	83.6 %	< 600 ms	Natural language help
Report Analyser	AI + PDF Parse	85.0 %	< 500 ms	Medical report insights

Performance metrics across five core modules under standard single-user conditions.

C. Predictive Metrics

Table II presents precision, recall, and F1-score for the four AI-driven modules.

TABLE II
Predictive Evaluation Metrics

Module	Precision	Recall	F1-Score
Disease Prediction	0.88	0.87	0.87
Scheme Recommendation	0.93	0.90	0.91
Chatbot Response	0.85	0.82	0.84
Report Analyser	0.86	0.84	0.85

Precision, Recall, and F1-Score for AI-driven modules on held-out test sets.

The scheme recommendation module achieves the highest F1-score (0.91) reflecting the deterministic nature of rule-based eligibility matching. The disease prediction module achieves 0.87, consistent with the performance envelope reported for comparable symptom-based classifiers in the literature [7][8]. The chatbot module records the lowest F1-score (0.84), attributable to natural language variability in query phrasing outside the training intent set.

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VII. COMPARATIVE ANALYSIS

Table III compares Accessible Assist against four existing digital health platforms across six feature dimensions.

TABLE III
Feature Comparison: Accessible Assist vs. Existing Platforms

Feature	Accessible Assist	NHA Portal	Practo	mySejahtera	eSanjeevani
Disease Prediction	Yes	No	Partial	Yes	No
Govt. Scheme Recommendation	Yes	Yes	No	Partial	No
Personalised Eligibility Check	Yes	No	No	No	No
AI Chatbot	Yes	No	Yes	Partial	No
Report Analyser	Yes	No	Yes	No	No
Open / Free Access	Yes	Yes	No	Yes	Yes

Feature comparison across six dimensions of citizen-focused healthcare platform functionality.

Accessible Assist is the only evaluated platform satisfying all six feature dimensions simultaneously. The National Health Authority portal provides scheme information but lacks personalised eligibility checking and disease prediction. Practo offers symptom-based consultation and report analysis but is a commercial service with no government scheme integration. eSanjeevani focuses exclusively on telemedicine, while mySejahtera (Malaysia's COVID health app) offers partial disease tracking without scheme recommendation. Accessible Assist uniquely combines all capabilities as a free, open platform.

VIII. LIMITATIONS

The disease prediction module produces indicative risk assessments and is not a substitute for professional clinical diagnosis. Predictions depend on the accuracy and completeness of user-supplied parameters; erroneous inputs will degrade output reliability. The scheme database is manually curated and requires periodic updates as government policies evolve. The system requires active internet connectivity and does not currently support offline operation. Evaluation metrics are based on structured test cases rather than large-scale randomised clinical trials, which limits the generalisability of reported performance figures.

The chatbot knowledge base covers a defined set of intents; queries substantially outside this scope receive fallback responses. Multi-language support is not implemented in the current version, limiting accessibility for users whose primary language is not English or Hindi.

IX. CONCLUSION

This paper presented Accessible Assist, a unified web-based platform that integrates AI-driven disease risk prediction, personalised government health scheme recommendation, and a conversational chatbot to improve healthcare accessibility for Indian citizens. The system addresses a well-documented gap in the existing landscape: the absence of a single, free, user-friendly platform that combines early health risk awareness with actionable welfare scheme discovery.

Evaluation across five modules confirmed predictive F1-scores above 0.84 and sub-600 ms response latency for all interactive features. Comparative analysis established that no existing platform offers an equivalent combination of disease prediction, personalised scheme eligibility, AI chatbot support, and report analysis under a free and open access model.

Future work will extend the platform through wearable device integration for real-time health monitoring, location-based scheme filtering by state and district, voice input for low-literacy users, offline operation capability, expanded multi-language support, and an emergency alert feature providing rapid access to nearby health facilities.

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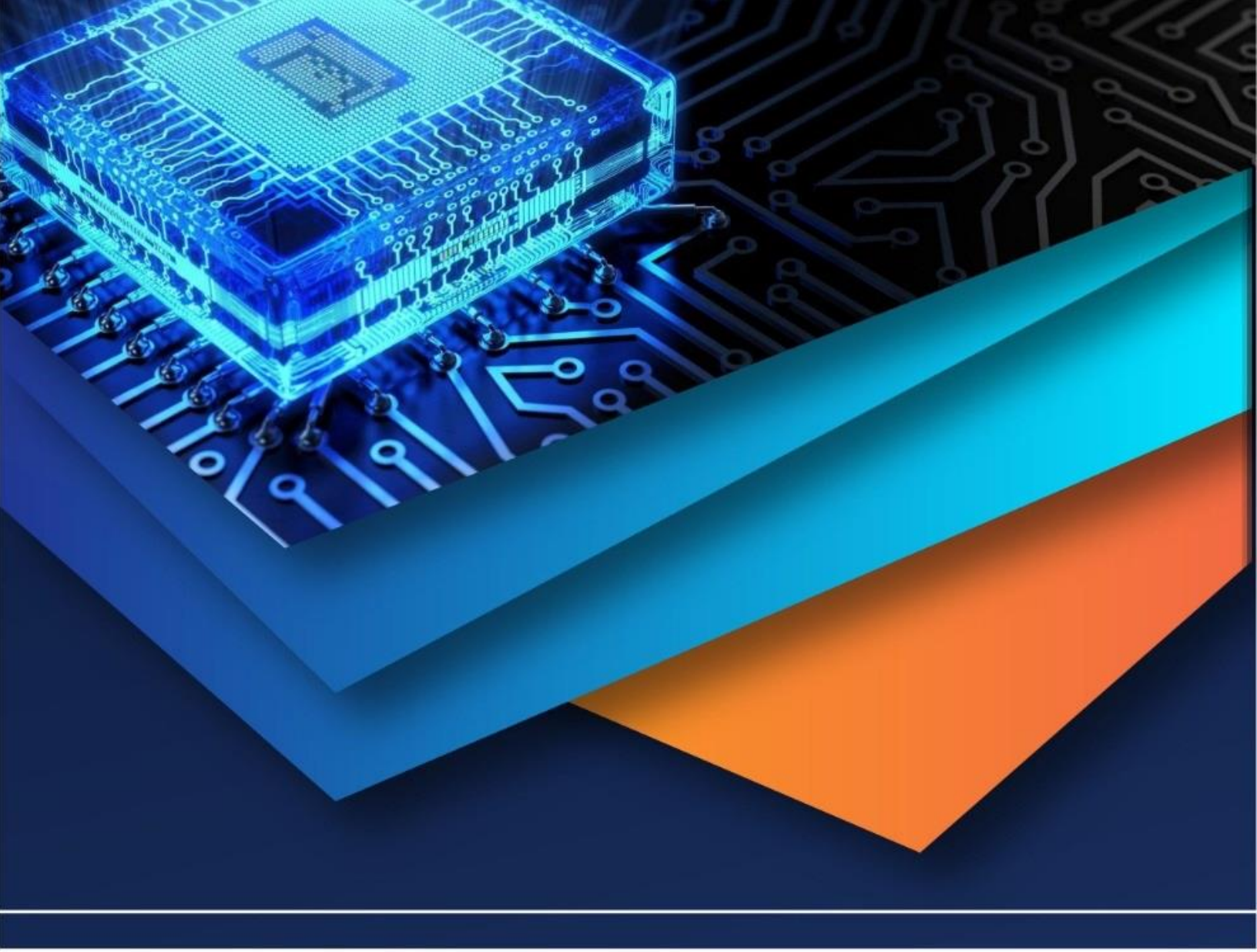

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