IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 11, Issue 8, August 2024

DOI: 10.17148/IARJSET.2024.11840

A Digital Health Management System for Rural Sub-Centres

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Abstract: An innovative digital health management system has been designed with the intent of improving healthcare services in rural sub-centres. It allows health workers to register individuals and automatically generate unique IDs, streamlining the tracking and updating of patient medical records across different levels of care. By utilizing sequential ID generation, the system employs an auto-incremental ID generation feature within the database to assign each patient a distinct identifier upon registration, thereby facilitating efficient data management and patient follow-up. This system specifically focuses on diabetes and hypertension; it gathers comprehensive health data and utilizes a multinomial logistic regression model to categorize patients' health conditions as healthy, diabetic, hypertensive, or both diabetic and hypertensive. Based on these classifications, health workers can create personalized lifestyle management plans tailored to each individual's health needs. For infants and children under 18, the system offers detailed immunization charts, while pregnant women receive vaccination schedules and nutrition guidelines to ensure comprehensive prenatal care. In more complex cases, health workers can refer patients to doctors at Primary Health Centres (PHCs), and if advanced diagnostics or specialized treatments are required, PHCs can further refer patients to hospitals. The unique ID facilitates seamless information sharing and updates among sub-centres, PHCs, and hospitals, enhancing continuity of care and improving health outcomes in rural areas. This integrated approach aims to bridge the healthcare gap in underserved regions by leveraging data and predictive analytics to provide targeted and effective healthcare services.

Keywords: Digital Health Management System, Rural Healthcare, Unified Patient ID System, Predictive Analytics, Multinomial Logistic Regression

I. INTRODUCTION

There are many factors that could limit access to health services in rural areas, including inadequate infrastructure, a lack of medical personnel, and logistical problems. Sub-centres, which serve as the first point of contact for the rural population, play a crucial role in delivering primary healthcare services. This paper introduces a comprehensive digital health management system specifically designed for sub-centres to improve the efficiency and effectiveness of healthcare delivery. The system focuses on addressing the prevalent health issues of diabetes and hypertension while also providing vital services for maternal and child health. By leveraging technology, this system aims to improve patient tracking, health data collection, and predictive analytics to provide personalized and continuous care. Chronic diseases like diabetes and hypertension are prevalent in rural areas due to a combination of factors, including limited access to healthcare services, lower health literacy, and socioeconomic constraints. These conditions, if not managed effectively, can lead to severe complications and increased mortality rates. The traditional healthcare infrastructure in rural settings often lacks the capacity for comprehensive data collection, continuous monitoring, and personalized patient care, exacerbating the problem.

Rural healthcare faces numerous real-time challenges that impede the delivery of quality services. One of the major issues is the lack of efficient patient tracking and record-keeping systems, leading to fragmented care and the loss of critical health information. Additionally, the high prevalence of chronic conditions such as diabetes and hypertension in rural populations is often compounded by delayed diagnosis and inadequate management. Health workers in sub-centres also struggle with providing timely immunizations and prenatal care due to insufficient data and resource constraints. The referral system for complex cases is often inefficient, causing delays in treatment and worsening health outcomes. These challenges highlight the urgent need for an integrated approach to streamline healthcare delivery in rural areas. The proposed system will facilitate the generation of unique patient IDs, ensuring accurate and accessible health records. Field workers will play a crucial role in collecting health data from rural residents, screening for chronic conditions, and implementing lifestyle modification plans for identified patients. Additionally, the platform will offer preventive care tools, such as immunization schedules for children and dietary guidelines for pregnant women, to promote overall community health.

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This journal proposes a comprehensive digital health management system as a solution to these problems. By introducing a unique ID system for each patient, health workers can efficiently register individuals and maintain up-to-date medical records accessible across sub-centres, PHCs, and hospitals. The system incorporates a multinomial logistic regression model to classify patients' health statuses, enabling health workers to create personalized lifestyle management plans for those with diabetes and hypertension. For infants, children, and pregnant women, the health workers provide immunization charts, vaccination schedules, and nutrition plans to ensure comprehensive care. Additionally, the system facilitates referrals to higher levels of care for complex cases, ensuring that patients receive the appropriate treatment and follow-up. This integrated approach addresses the gaps in rural healthcare delivery, aiming to improve health outcomes and the overall quality of care for rural populations.

II. LITERATURE REVIEW

A. Unique ID Generation

In the context of digital health management systems, the generation of unique identifiers in databases plays a pivotal role in ensuring efficient healthcare delivery and seamless patient management. Numerous studies have explored different approaches and techniques for generating and managing unique patient identifiers, offering insights into their feasibility, reliability, and effectiveness in facilitating healthcare delivery in resource-limited settings.

1) Sequential ID generation:

In sequential ID generation, patients are given unique identifiers in a sequential manner. Normally, this is usually based on an increasing numerical value following a predefined pattern. Several studies show simplicity and efficiency of sequential ID generation, the implementation may be from simple integer sequences up to complex alphanumeric forms.

2) Universally Unique Identifier (UUID):

UUID is a standardized methodology for the generation of unique IDs, and it had significant interest from health care systems due to its strength of robustness and uniqueness. Studies have been made on the application of UUIDs for automatic ID generation of patient records so that unique identifiers could be created by the distributed systems without centralized coordination. UUIDs offer a good resistance against collision and are suitable in scenarios where uniqueness is paramount, such as patient identification in healthcare databases.

3) Timestamp-Based IDs:

Timestamp-based IDs are a way to make use of time information in coming up with unique identifiers, usually by associating timestamps or date-time values into the generation of IDs. Literature is written that looks into timestamp-based IDs relating to the tracking of patient encounters, appointments, and medical events. This facilitates chronological sorting and retrieval for health records. Healthcare systems can manage data efficiently and track time changes in patients' information by encoding time information within these IDs.

4) Biometric-based IDs:

Biometric-based identification systems provide a new dimension to automatic ID generation by using unique physiological or behavioural traits of an individual. Research follows through in the use of biometric identifiers, such as fingerprints, iris scans, and face recognitions for patient identification at healthcare settings. Biometric-based IDs could ensure more secure and accurate healthcare compared to the traditional methods of patient identification and might even help resolve problems associated with duplicate records and identity theft.

5) Blockchain-based IDs:

The blockchain has also been very instrumental in the automatic generation and management of IDs or as a method of identification, mostly due to the decentralized state and tamper resistance of data storage within it. Accordingly, the present research investigates the applicability of blockchain-based systems for patient identity management by offering a scheme through which patients can be uniquely identified across different healthcare providers and information systems while ensuring high security and auditability for the integrity and privacy of patient identifiers based on the immutability and cryptographic properties of blockchain technology in healthcare systems.

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B. Classification algorithms

In rural healthcare management, classification of diseases becomes imperative to administer proper and timely treatment to patients. The machine learning algorithms provide valuable tools to automate this task by using the data available about the patient in predicting and classifying their health condition. Through predictions, it enables healthcare providers in rural sub-centres to make informed decisions based on data-driven insights.

1) Logistic Regression:

Logistic regression stands as one of the basic classification algorithms in healthcare analytics, even including rural healthcare management. Recent literature still proves its efficiency in predicting binary or multinomial outcomes based on patient characteristics. On the other hand, logistic regression is relatively easy to comprehend and implement; it is therefore more appropriate for settings with limited computational resources and expertise. Studies have established logistic regression as one of the tools applied in rural sub-centres for the prediction of health conditions such as diabetes and hypertension, hoping that with it shall come insight into the variables that influence health outcomes.

2) Binary Logistic Regression:

Binary logistic regression constitutes one of the fundamental basics in modelling binary outcomes with the absence and presence of a disease in health care analytics. The current research further indicated efficacy of this tool within rural health care settings since it allows for proper patient stratification for purposes of planning proper interventions. The method is thus simple, interpretable, and computationally efficient, which makes it appropriate for resource-constrained environments. Other studies have deployed binary logistic regression models within the sub-centres to predict possible health conditions most residents are likely to suffer from, like diabetes, in the process indicating that it is possible to identify in advance most-at-risk individuals for focused intervention measures.

3) Multinomial Logistic Regression:

Multinomial logistic regression has value in health care analytics for predicting outcomes with more than two categories, like categorizing patients according to multiple health conditions. Recent research demonstrated that it was applicable in rural healthcare management, whereby the classification of a patient in disparate health categories is necessary for intervention planning. In such a sense, multinomial logistic regression returns flexibility and interpretability to stratify patient risk and hence becomes useful for health care providers to use their resources. - multinomial logistic regression has been used in studies within rural sub-centres for classification of patients into various categories concerning their health.

4) Decision Trees:

In the recent research in rural healthcare management, decision trees have become one of the important tools in the classification of patients. They provide very intuitive decision procedures by recursively partitioning the feature space against patient characteristics. Recent applications have shown that decision trees can handle heterogeneous data types and capture complex relations between patient attributes and health conditions. The application of decision trees in rural sub-centres has been applied in classifying patients to different health categories for the purpose of tailoring interventions and hence resource allocation for healthcare workers.

5) Random Forests:

Recent advances in rural healthcare management have strongly adopted random forests for patient classification tasks. Random forests are ensemble learning, a method combining multiple decision trees to improve the accuracy and robustness of the classification. Random forests have been recently shown to perform well on big and noisy health data sets typical of rural settings. In a nutshell, random forests use aggregation of predictions from diverse decision trees so as to give better generalization performance and insight into the relative importance of different attributes of patients for predicting the outcome in health.

6) Naive Bayes:

Recent studies in rural healthcare management have revealed the applicability of Naive Bayes classifiers in the classification of patients. A Naive Bayes classifier is a simple probabilistic classifier based on Bayes' theorem and is

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used for predicting the health status of a patient from his/her attributes. Recent research has proven that Naive Bayes is simple and efficient while handling big and noisy healthcare datasets. Applications of Naive Bayes Classifiers in the classification of patients across various health categories in rural sub-centres have contributed immensely to insight likelihood estimates of specific health conditions given patient characteristics.

7) Support Vector Machines (SVM):

Recent research in rural healthcare management has underscored the flexibility of SVM in patient classification. It excels at separating patients with different health conditions by seeking an optimal hyperplane in high-dimensional feature space. Some recent studies have further demonstrated its efficiency when there are nonlinear relationships between patient attributes and health conditions. In rural sub-centres, SVMs have been applied in the classification of patients according to demographic, clinical, and lifestyle factors, which allows appropriate planning of interventions and delivery of health care that is tailor-made.

III. METHODOLOGY

A. Block Diagram

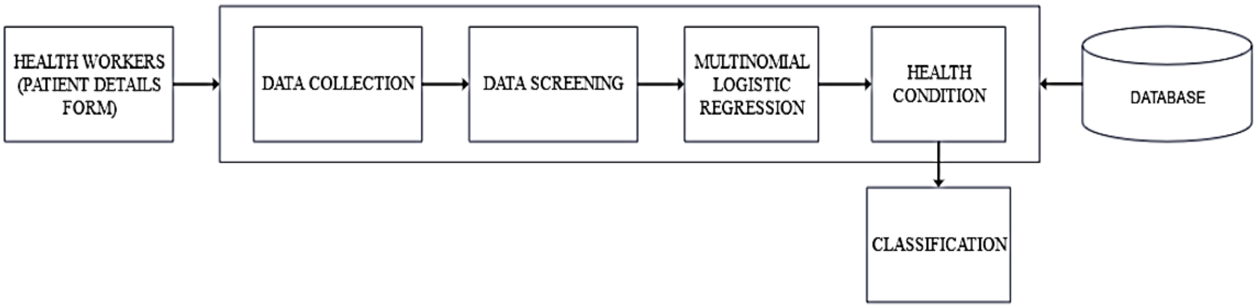

Fig 1: Multinomial Logistic Regression Algorithm

The process begins with health workers using patient details forms to collect initial health data from individuals, including basic personal information and relevant health metrics, particularly focusing on diabetes and hypertension. This collected data then undergoes a data collection phase where it is systematically gathered and stored. Next, in the data screening phase, the gathered information is meticulously checked for accuracy, completeness, and consistency to attain high-quality data to further analyse. At the next stage, with the application of a multinomial logistic regression model, comes the screened data so as to classify patients into different health conditions like healthy, diabetic, hypertensive, or both diabetic and hypertensive. The classified health conditions are then recorded and stored in a central database.

B. Data Collection

The first step involves data collection. Health workers at rural sub-centres gather essential personal information (age, gender, etc.) from every resident within their jurisdiction. They fill out a digital form for each person, registering their details. Once registration is complete, the system automatically generates a unique ID for each individual. This ID is created using a sequential auto-incremental feature within the database. This unique ID is then stored in a central database, connecting all future health data and records to it. Following the registration of personal details, health workers proceed to collect health-related information (blood pressure readings, glucose levels, weight, etc.) and record it digitally.

C. Data Screening

Data screening is the careful examination and preprocessing of collected health data to ensure that it is accurate, complete, and consistent. This step cleans up the data, including error removal and replacement of missing values, in a way that ensures high accuracy of the data and standardization of format so that it perfectly fits into predictive analytics models. In doing so, the system will be working on reliable information that has been obtained through effective screening of the data and validated for further analysis to enhance accuracy in health condition classifications and subsequent healthcare interventions.

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D. Multinomial Logistic Regression Algorithm

Step 1: Feature Selection

Feature selection methods use statistical methods and domain knowledge in the selection process to isolate health indicators relevant for health outcome predictions from the screened data. For example, age, blood pressure, blood glucose levels, BMI, and other health indicators relevant for predicting an outcome are taken into consideration. This stage cuts down on dimensionality, hence making the model more efficient and effective by focusing on those attributes that are most predictive.

Step 2: Probabilities Calculations

When patient data is entered or updated, the model processes the input features and computes the probability of the patient belonging to each health condition category (healthy, diabetic, hypertensive, or both). This calculation ensures that the subsequent classification is accurate and based on the most current patient data available.

Step 3: Health Condition Classification

The model assigns the health condition with the highest probability to the patient. With classification, it is possible to indicate whether a patient is healthy, diabetic, hypertensive, or both. These will hence enable health workers to provide a lifestyle management plan covering each requirement that the patient needs.

Step 4: Data Storage and Access

All collected data, and classification results are securely stored in a centralized database. The database allows easy retrieval and updating of patient records by health workers and healthcare providers with the right authorities. Hence, very tight measures will be taken in ensuring security to protect patients' privacy and avoid health sector regulation violations.

Step 5: Continuous Monitoring and Updates

At follow-up visits, health workers update information about patients and the system reflects the most recent health data. Indeed, the data is updated once more in the multinomial logistic regression model to adjust management plans if necessary. Therefore, it is a continuous process of keeping healthcare interventions relevant and effective as changes occur in a patient's health status.

E. Database Integration

By integrating these databases, the healthcare management system furnishes a comprehensive framework for collecting, storing, and using health data in support of full-scale and effective healthcare delivery in rural areas.

User Database: The User Database stores comprehensive information about the health workers and other users involved in the healthcare management system. This includes essential details such as names, roles, contact information, and their associated sub-centres. By maintaining accurate and up-to-date records of all personnel, the system ensures seamless communication and coordination among healthcare providers, facilitating efficient data entry, patient monitoring, and follow-up processes.

Patient Database: The Patient Database is crucial for storing the personal and health-related information of all registered residents. Each patient is assigned a unique ID, linking their demographic details and health metrics. This database serves as the central repository for patient information, allowing health workers to easily access and update records during visits. It ensures that all collected data is systematically organized, supporting effective tracking of patient health status and history.

Health Data Database: The Health Data Database contains detailed records of patients' health metrics, including blood pressure readings, glucose levels, weight, and other vital signs. This database ensures that all collected health data is meticulously stored and easily retrievable for analysis. It plays a pivotal role in the data screening process, where health data is cleaned, standardized, and prepared for predictive modelling, ensuring high data quality for accurate health condition classifications.

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Diagnosis Database: The Diagnosis Database stores the results of the multinomial logistic regression analysis, including the predicted health conditions for each patient. It records detailed diagnostic information, such as the probabilities of being healthy, diabetic, hypertensive, or both. This database facilitates the classification of health conditions, enabling health workers to identify the appropriate interventions for each patient based on the model's predictions.

Management Plan Database: The Management Plan Database manages personalized lifestyle and health management plans for patients. It includes recommendations for diet, exercise, medication, and other lifestyle modifications tailored to each patient's diagnosed health condition. This database ensures that health workers can create, store, and update individualized care plans, supporting ongoing patient management and improving health outcomes through targeted interventions.

Referral Database: The Referral Database manages the referral process for patients requiring advanced care. It stores detailed information about referrals from sub-centres to PHCs and hospitals, including reasons for referral, dates, and specialist notes. This database ensures that patient transitions between different levels of care are well-documented and coordinated, facilitating efficient follow-up and specialized treatment as needed.

PHC Database: The PHC Database contains information about primary health centres and their healthcare providers. It includes details such as the names, locations, and contact information of PHCs and their doctors. This database ensures that health workers can easily access information about nearby PHCs, enabling timely referrals and consultations for patients requiring primary healthcare services.

Hospital Database: The Hospital Database maintains records of hospitals and their specialists. It includes information about hospital locations, contact details, and the specializations of healthcare providers. This database is essential for managing referrals to hospitals for advanced diagnostics and specialized care, ensuring that patients receive the necessary treatment from the appropriate medical experts.

Overall, the utilization of databases across different modules in the digital health management platform facilitates efficient data management, seamless information exchange, and improved healthcare delivery for rural populations.

IV. PROPOSED SYSTEM

The proposed system is an integrated online platform designed to enhance healthcare delivery in rural areas through efficient data management and predictive analytics. This platform features comprehensive modules for patient registration, health data collection, screening, diagnosis, and management of personalized care plans. By employing advanced machine learning algorithms, specifically multinomial logistic regression, the system aims to accurately classify patients' health conditions and provide tailored healthcare interventions. The system facilitates seamless coordination among sub-centres, PHCs, and hospitals, ensuring continuous and connected patient care.

A. Working Principle

The system operates by guiding health workers through patient registration and data collection at rural sub-centres. Workers capture essential personal details through a digital form, generating a unique ID for each patient using a sequential auto-incremental feature in the database. This ID links all health data to the patient, including metrics like blood pressure and glucose levels. The collected data undergoes screening to ensure accuracy, involving data cleaning, error handling, and standardization. The multinomial logistic regression algorithm is applied to classify health conditions, training on historical data, validating its performance, and calculating the probabilities of each health condition (healthy, diabetic, hypertensive, or both). Based on these classifications, health workers generate personalized healthcare plans with specific recommendations on diet, exercise, and medication. For children, immunization charts are provided, while pregnant women receive vaccination schedules and nutrition charts. All data, including patient details, health metrics, diagnoses, and care plans, is securely stored in a centralized database accessible to authorized health workers and healthcare providers. In complex cases, patients are referred to doctors at PHCs or hospitals, with the unique patient ID ensuring coordinated and efficient treatment. This approach ensures comprehensive healthcare management, leveraging technology to improve health outcomes and streamline healthcare delivery in rural areas.

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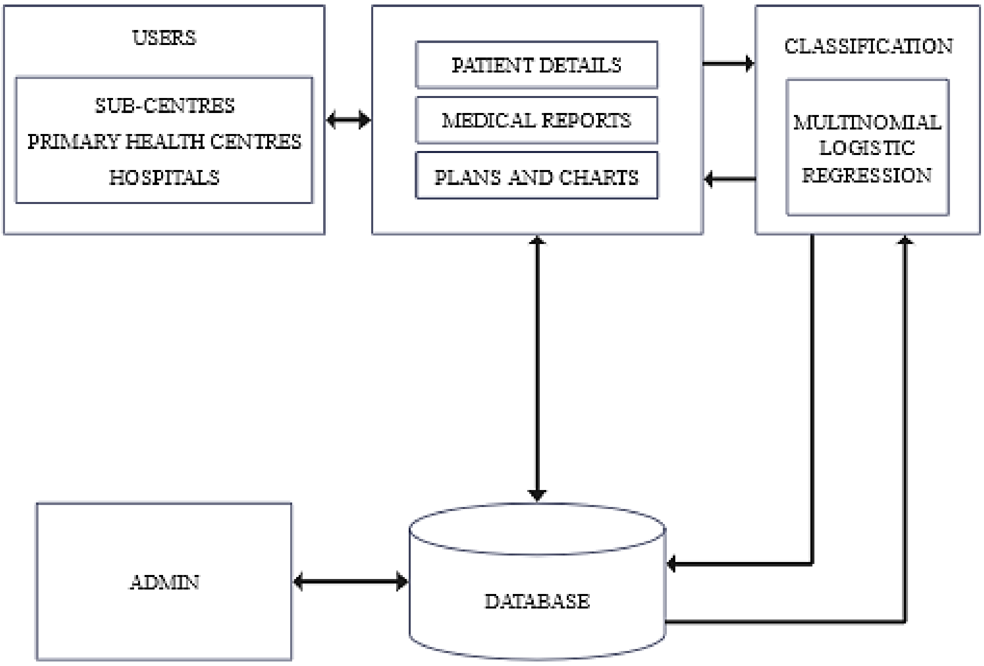

Fig 2: System Architecture

B. Algorithms

1) Multinomial Logistic Regression Algorithm:

Input: Health Data from Patient Records

The Multinomial Logistic Regression algorithm relies on health data inputs collected from patient records. These inputs include key health metrics such as blood pressure readings, glucose levels, weight, age, and gender, collected during patient registration and follow-up visits.

Process: Health Condition Classification

The multinomial logistic regression algorithm processes the input data by analysing the relationships between the extracted features and the likelihood of various health conditions. It estimates the probabilities of each outcome category as calculated by equation (1), including no diabetes or hypertension, diabetes only, hypertension only, and both diabetes and hypertension, based on the input features. Through iterative optimization, the algorithm determines the coefficients that best fit the data and classifies patients into the appropriate health condition categories.

$$P(Y = k|X) = \frac{e^{X\beta_k}}{\sum_{j=1}^{K} e^{X\beta_j}}$$

$P(Y = k|X)$ = the probability of the patient Y belonging to category k given the input features X

e = the base of the natural logarithm.

j = the summation index representing each of the K possible categories.

K = the total number of categories.

β_k = the vector of coefficients associated with category k

$X\beta_k$ = the dot product of the input feature vector X and the coefficient vector β_k.

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$e^{X\beta_k}$ = the exponentiation of the linear combination of features and coefficients.

$\sum_{j=1}^{K} e^{X\beta_j}$ = the sum of the exponentiated linear combinations for all categories.

Output: Health Condition

The output of the multinomial logistic regression algorithm is the predicted health condition category for each patient based on their input features. Patients are classified into one of the defined categories, providing valuable insights into their health status and risk factors. This output guides the creation of personalized intervention strategies, such as lifestyle modification plans and preventive care measures, tailored to each individual's specific health needs. Additionally, the output facilitates the seamless referral of patients to healthcare professionals and hospitals for further evaluation and treatment, ensuring timely and targeted healthcare interventions in rural communities.

V. MODULE IMPLEMENTATION

A. USER

1) Login:

Users begin their journey on the login page. Here, the users, typically health workers, PHCs, and hospitals login through their credentials provided by admin.

2) User Dashboard:

After logging in, users access the main dashboard, which provides several key modules.

Patient Management Module: Health workers register patients by collecting personal details (name, age, gender, and address) and automatically generating a unique patient ID. They can also search for patients using their unique ID or personal details and update their medical records as needed. This module provides a detailed history of each patient’s medical records, and treatments, ensuring efficient data management and patient follow-up.

Health Data Collection Module: Health workers collect and enter comprehensive health data for each patient, focusing on key parameters like blood pressure, blood sugar levels, BMI, and medical history. The system uses a multinomial logistic regression model to classify patients into categories: healthy, diabetic, hypertensive, or both diabetic and hypertensive. Based on the classification, the health workers can provide personalized lifestyle management plans, which to patients.

Immunization and Prenatal Care Module: This module provides detailed immunization schedules for infants and children under 18, ensuring they receive timely vaccinations. It also offers pregnant women vaccination schedules and nutrition charts, ensuring comprehensive prenatal care. Health workers can use this information to monitor and manage immunization and prenatal care efficiently.

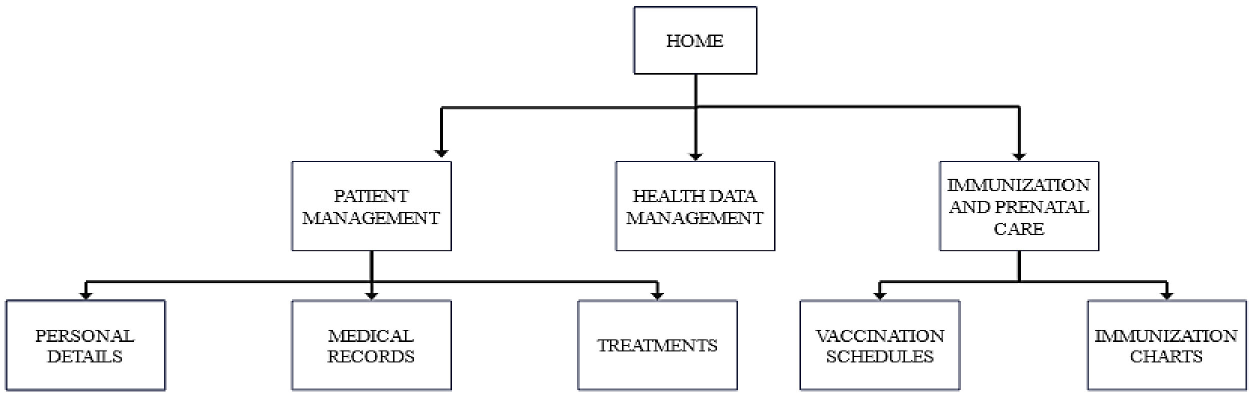

Fig 3: User Sitemap Diagram

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B. ADMIN

1) Login:

Administrators access the system through a dedicated login page. Upon logging in, they can manage various aspects of the platform via the admin dashboard, ensuring smooth operation and maintenance of the platform.

2) Admin Dashboard:

User and Patient Profiles Module: This module allows admins to view detailed profiles of all users, including health workers and administrators. Admins can also view comprehensive profiles of all registered patients, including their medical history and interactions with the health system, enabling them to track user engagement and address any issues that arise.

Health Data Management Module: Admins can validate and approve health data entries to ensure accuracy and consistency. They can also update the multinomial logistic regression model with new data to improve classification accuracy, ensuring the system remains reliable and effective.

Reports Module: This module generates comprehensive reports on the health status of the population, including trends in diabetes and hypertension. It also provides metrics on the performance of health workers and the overall health management system, helping admins to monitor and improve service delivery.

User Login Management Module: Admins are responsible for creating and managing login credentials for sub-centres, PHCs, and hospitals. This module allows admins to create, update, and delete user accounts, ensuring that only authorized personnel have access to the system. It also facilitates role-based access control, ensuring that users have appropriate permissions based on their role within the healthcare system.

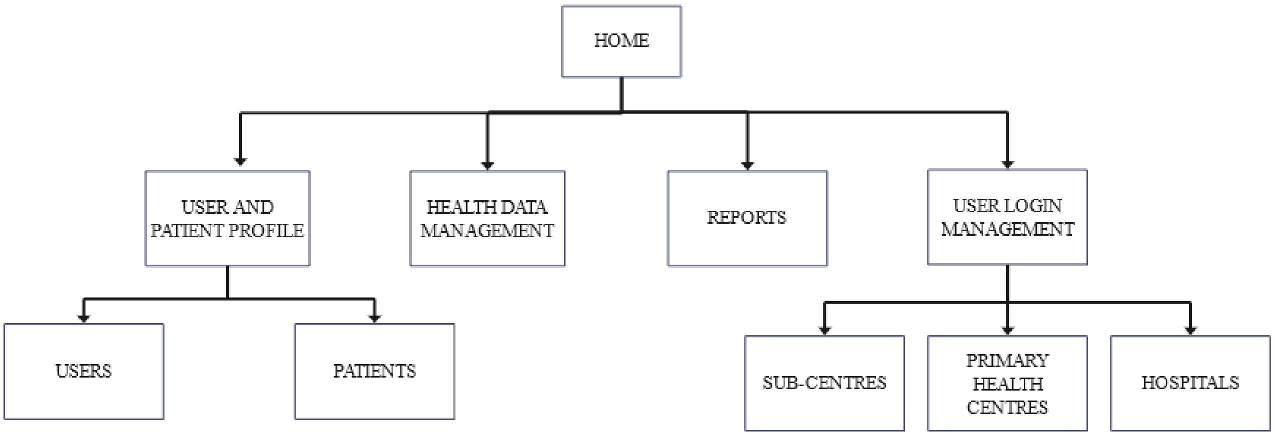

Fig 4: Admin Sitemap Diagram

VI. CONCLUSION

The development of an innovative digital health management system aims to enhance healthcare delivery in rural sub-centres. By enabling health workers to register individuals and automatically generate unique IDs, the system streamlines the tracking and updating of patient medical records across different levels of care. Utilizing sequential ID generation and a robust database, the system ensures efficient data management and patient follow-up. The inclusion of a multinomial logistic regression model allows for precise classification of patients' health statuses into categories: healthy, diabetic, hypertensive, or both diabetic and hypertensive. This classification helps health workers create personalized lifestyle management plans tailored to individual health needs, improving the quality of care. The system also provides detailed immunization charts for infants and children under 18 and comprehensive prenatal care schedules for pregnant women, ensuring holistic healthcare services. In complex cases, the referral system enables seamless information sharing and updates among sub-centres, PHCs, and hospitals, thus enhancing continuity of care and improving health outcomes in rural areas. The integrated approach aims to bridge the healthcare gap in underserved regions by leveraging data and predictive analytics to provide targeted, efficient, and effective healthcare services. Future developments could include

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incorporating advanced machine learning algorithms and real-time data analytics to further improve the accuracy of health status predictions and provide even more personalized healthcare recommendations. Additionally, expanding the system to cover more diseases and health conditions could broaden its impact, making it a comprehensive tool for rural healthcare management.

In conclusion, the implementation of the multinomial logistic regression model in the proposed digital health management system has resulted in a notable improvement in classification accuracy compared to traditional methods. Previously, classification algorithms like binary logistic regression and decision trees achieved accuracy rates typically ranging from 60% to 75%. However, with the adoption of multinomial logistic regression, accuracy has significantly increased to a range of 80% to 95%, marking an improvement of approximately 20%. This enhanced accuracy facilitates more precise and individualized patient care, enabling health workers to better manage diabetes and hypertension in rural settings. The system's ability to classify patients into specific health categories—healthy, diabetic, hypertensive, or both—supports tailored healthcare interventions, ultimately contributing to better health outcomes and more efficient resource allocation in underserved rural areas.

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