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AyurCard: An AI-Driven Unified Healthcare Ecosystem for Centralized Medical Record Management and Intelligent Disease Prediction

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***Abstract*— The advancement of digital healthcare technologies has emphasized the need for centralized healthcare record management, secure information sharing, and intelligent clinical decision support. The AyurCard, as a unified digital healthcare ecosystem that provides each patient with a unique AyurCard-ID for managing healthcare information through a centralized platform. The framework securely connects patients, doctors, authorized medical stores, and administrators, enabling electronic health record management, digital prescriptions, appointment scheduling, prescription traceability, and role-based access control. To support preventive healthcare and clinical decision-making, the system integrates Random Forest and XGBoost machine learning models for predicting potential chronic and acute disease risks using patient healthcare records, clinical parameters, and symptom data. The generated risk probabilities and health insights assist healthcare professionals in evaluating patient conditions and supporting timely medical intervention. By combining centralized healthcare management with AI-assisted disease prediction, AyurCard aims to improve healthcare accessibility, continuity of care, transparency, and overall healthcare service efficiency while providing a secure and scalable digital healthcare infrastructure.**

***Keywords*— Artificial Intelligence in Healthcare, Machine Learning, Random Forest, XGBoost, Chronic Disease Prediction, Acute Disease Prediction, Electronic Health Records (EHR), Predictive Healthcare, Centralized Healthcare System, Clinical Decision Support System.**

I. INTRODUCTION

Healthcare systems often face problems such as scattered medical records, repeated diagnostic tests, delayed access to patient history, and limited coordination between healthcare stakeholders. As patient information is usually stored across different hospitals, clinics, and laboratories, doctors may not always have access to a complete medical history during treatment. To address these challenges, AyurCard, as a unified digital healthcare ecosystem that assigns a unique digital health identity to every patient. Using the AyurCard ID, all medical information including diagnosis records, prescriptions, laboratory reports, and treatment history is securely stored and managed in a centralized system. The proposed framework connects patients, doctors, authorized medical stores, and administrators on a single platform [1]. Doctors can access patient records, update diagnosis information, and generate digital prescriptions.

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Authorized medical stores can access prescription-related information, while patients can view their medical history, appointments, and healthcare records through their dashboard. To further support healthcare decision-making, AyurCard integrates machine learning models, namely Random Forest and XGBoost, for chronic and acute disease prediction. The generated health insights help doctors analyze potential disease risks using historical and recent clinical data. By combining centralized medical record management with AI-assisted healthcare support, AyurCard aims to improve healthcare accessibility, continuity of care, transparency, and overall healthcare efficiency [2] [3].

II. METHODOLOGY

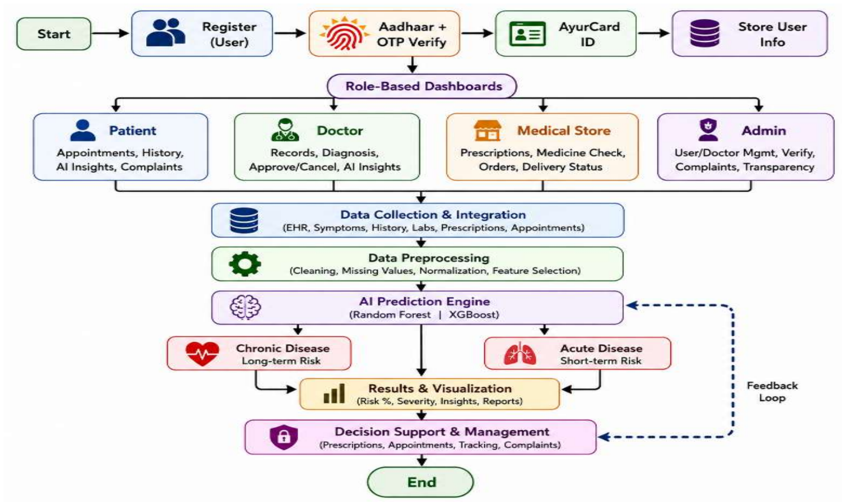

Fig. 1 Proposed methodology for Ayurcard

The proposed AyurCard framework follows a workflow-based approach that integrates healthcare record management with AI-assisted disease prediction. The overall methodology consists of the following stages.

Step 1: Registration and AyurCard ID Generation

Patients, doctors, authorized medical stores, and administrators register on the platform using Aadhaar verification and OTP authentication. After successful verification, a unique AyurCard ID is generated for each patient. The ID serves as a digital health identity and links all future healthcare records.

Step 2: Medical Record Creation and Storage

When a patient visits a hospital, the doctor accesses the patient's profile using the AyurCard ID and records symptoms, diagnosis details, laboratory reports, prescriptions, and consultation status. The information is securely stored in a centralized electronic health record database.

Step 3: Data Collection and Preprocessing

Patient healthcare records are collected from the centralized database. Before analysis, the data undergoes preprocessing, including missing value handling, normalization, feature selection, and data standardization to improve prediction quality.

Step 4: AI-Based Disease Prediction

The processed data is analyzed using Random Forest and XGBoost algorithms. Historical medical records are utilized for chronic disease prediction, while recent clinical data and symptom patterns are used for acute disease prediction. The generated predictions are represented through probability-based graphical visualization [4].

Step 5: Healthcare Management and Prescription Traceability

Doctors generate digital prescriptions and manage appointments through the platform. Authorized medical stores can securely access prescription-related information for medicine dispensing, ensuring privacy and prescription traceability.

Step 6: Patient and Administrative Services

Patients can view medical records, appointments, prescriptions, and AI-generated health insights through their dashboard.

Administrators monitor complaints, manage system activities, and ensure transparency and accountability within the healthcare ecosystem.

Step 7: Security and Performance Evaluation
The framework implements Aadhaar and OTP-based authentication, role-based access control, and encrypted healthcare data storage. The prediction models are evaluated using Accuracy, Precision, Recall, and F1-Score to measure their effectiveness. The proposed methodology enables secure healthcare record management, intelligent disease prediction, and efficient coordination among healthcare stakeholders through a unified digital healthcare ecosystem [5].

III. LITERATURE SURVEY

Recent advancements in artificial intelligence and machine learning have significantly enhanced disease prediction and diagnosis. Javed et al. [6] proposed an IoMT-enabled deep learning framework for Alzheimer's disease detection using MRI images. The approach combined U-Net segmentation with ResNet-101 and transfer learning, achieving 98.19% training accuracy and 96.06% validation accuracy, demonstrating the effectiveness of integrating IoMT and deep learning for medical diagnosis.
Data preprocessing is crucial for improving prediction performance. Ramadhan et al. [7] reviewed machine learning techniques for chronic disease prediction, emphasizing missing value handling, outlier detection, data balancing, and feature selection.
The study evaluated models such as Random Forest, XGBoost, AdaBoost, CatBoost, ANN, CNN, SVM, KNN, and Naïve Bayes, concluding that appropriate preprocessing substantially improves prediction accuracy and reliability.
Security remains a critical concern in digital healthcare systems. Halman and Alenazi [8] introduced a machine learning-based cyberattack detection framework for Software-Defined Networking (SDN) in healthcare environments. Using preprocessing techniques such as scaling and PCA, the system evaluated multiple classifiers, including Decision Tree, Random Forest, Logistic Regression, AdaBoost, and XGBoost, achieving F1-scores of 0.9998 for normal traffic and 0.9882 for attack detection.
Deep learning has also demonstrated effectiveness in healthcare analytics using limited datasets. Tran et al. [9] developed a predictive framework integrating few-shot learning, multitask learning, and autoencoder architectures. Evaluated on COVID-19 blood test and breast cancer datasets, the model outperformed traditional approaches such as Decision Tree, Logistic Regression, Random Forest, and Support Vector Classifier in both binary and multi-label classification tasks.
Furthermore, ensemble learning techniques have improved diagnostic accuracy. Anuradha et al. [10] proposed a liver disease prediction model using K-Nearest Neighbors, Decision Tree, and Artificial Neural Network classifiers combined through majority voting. Using the Indian Liver Patient Dataset, the ensemble approach achieved 96% accuracy, highlighting the potential of hybrid learning methods for early disease detection.
Although existing studies demonstrate the effectiveness of AI for disease prediction, a significant gap remains in developing integrated healthcare platforms that combine centralized electronic health records, secure access control, and AI-driven decision support.
AyurCard addresses gap by integrating medical record management, predictive analytics, and secure digital identity to support preventive and continuous healthcare.

IV. SYSTEM ARCHITECTURE

The AyurCard architecture is designed as a centralized healthcare platform that integrates secure medical record management, healthcare services, and AI-assisted disease prediction. The system connects patients, doctors, authorized medical stores, and administrators through a unified digital healthcare environment.
The architecture begins with User Authentication and Role-Based Access Control (RBAC), where stakeholders access the platform according to their assigned roles. After successful verification, the AyurCard ID Generation module assigns a unique digital identity to each patient, enabling all healthcare records to be linked under a single profile.
Patient information, medical history, laboratory reports, prescriptions, appointments, and diagnosis records are maintained within the Patient Data Management and Centralized Healthcare Database modules [11]. The collected healthcare data undergoes preprocessing, including data cleaning, normalization, feature extraction, and missing value handling, before being used for analysis.
The AI Health Insight Engine forms the core analytical component of the system. It utilizes Random Forest and XGBoost models trained on healthcare datasets to perform chronic and acute disease prediction. The generated results are processed through the Risk Assessment module to determine disease probability and severity levels.

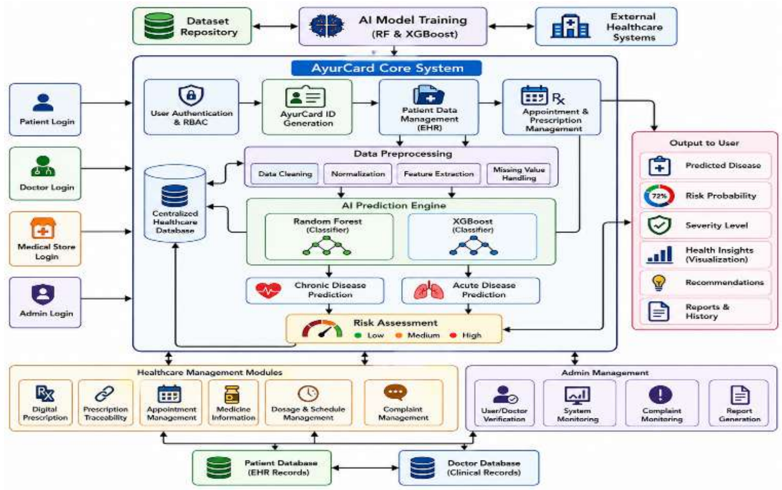

Fig. 2 Proposed Architecture for Ayurcard

The architecture also incorporates healthcare management services such as digital prescription management, prescription traceability, appointment scheduling, medicine information management, dosage scheduling, and complaint monitoring. Administrative functions including user verification, system monitoring, complaint handling, and report generation are managed through the Admin Management module [12] [13].
Finally, the system delivers disease predictions, risk assessments, health insights, recommendations, and medical reports to authorized users. The integration of centralized healthcare records, intelligent prediction models, and healthcare management services enables AyurCard to function as a secure, scalable, and patient-centric digital healthcare ecosystem [14].

V. ALGORITHMS

The xyurCard framework utilizes Random Forest and XGBoost models to predict chronic and acute disease risks from patient healthcare records. These models were selected because they perform effectively on structured healthcare datasets containing clinical parameters, symptoms, laboratory reports, and diagnosis history. Random Forest is used as the baseline prediction model, while XGBoost is used as the optimized prediction model. Their performance is evaluated and compared to determine the most suitable model for disease risk assessment [15] [16].

A. Random Forest-Based Prediction

Random Forest consists of multiple Decision Trees trained using randomly selected samples and features from the healthcare dataset. Each Decision Tree independently analyzes patient attributes such as age, blood pressure, glucose level, heart rate, cholesterol level, symptoms, and diagnosis history to generate a disease prediction. The outputs of all trees are combined through majority voting to produce the final prediction. The proportion of trees predicting a specific disease is used to calculate the disease probability score [17].

B. XGBoost-Based Prediction

XGBoost constructs Decision Trees sequentially, where each new tree learns from the prediction errors of the previous trees. The model iteratively minimizes prediction errors and updates the prediction score until improved performance is
achieved. The outputs of all trees are combined to generate the final disease probability score and risk estimation [18].

C. Algorithm: AyurCard Disease Prediction Framework

Input: Patient healthcare records, symptoms, laboratory reports, and clinical parameters.
Output: Disease risk probability, severity level, and health insights.
Steps:

- Retrieve patient healthcare records from the centralized AyurCard database.

- Extract clinical features including age, blood pressure, glucose level, heart rate, cholesterol level, symptoms, and diagnosis history.
- Perform data preprocessing through missing value handling, normalization, feature selection, and data standardization.
- Separate the processed data into:
  - Historical healthcare records for chronic disease prediction.
  - Recent clinical records and symptom patterns for acute disease prediction.
- Train Random Forest and XGBoost models using the prepared dataset.
- Generate disease probability scores through both prediction models.
- Evaluate model performance using Accuracy, Precision, Recall, and F1-Score.
- Select the model with the highest predictive performance.
- Classify disease risk into Low, Medium, or High categories.
- Generate risk scores, severity levels, and graphical health insights.

D. Risk Assessment

The selected prediction model generates disease probability scores that are converted into risk levels. The final results are presented through graphical visualization and healthcare insights to support disease risk assessment and clinical decision-making [19].

VI. MATHEMATICAL MODEL

The AyurCard framework utilizes machine learning models to analyze patient healthcare records and estimate disease risks. Let the patient healthcare record be represented as:

$$X = \{x_1, x_2, x_3, ..., x_n\}$$

where x_i represents clinical features such as age, blood pressure, glucose level, heart rate, cholesterol level, symptoms, and diagnosis history.

A. Random Forest Model

Random Forest is an ensemble learning model consisting of multiple Decision Trees. Each Decision Tree independently analyzes the patient healthcare record and generates a disease prediction.
The prediction generated by the ith Decision Tree is represented as:
$T_i(X) = y_i$
where:
T_i = ith Decision Tree, y_i= predicted disease class
The final Random Forest prediction is obtained through majority voting among all Decision Trees and is represented as:

$$Y\_RF = \text{Mode}\ \{T_1(X), T_2(X), ..., T_n(X)\}$$

where:
Y_RF = final Random Forest prediction, n = total number of Decision Trees
The probability of the predicted disease class is calculated as:

$$P\_RF = Nc / N$$

where:
Nc = number of trees predicting a particular disease class, N = total number of trees
The probability score is used for disease risk estimation.

B. XGBoost Model

XGBoost is a gradient boosting model that constructs Decision Trees sequentially. Each new tree learns from the prediction
errors of the previous trees and improves the overall prediction performance.
The final prediction generated by XGBoost is represented as:

$$\hat{Y} = \Sigma\ f_k(X)$$

where:

$f_k(X)$ = output of the kth Decision Tree
K = total number of trees, $\hat{Y}$ = final predicted output
The objective function minimized by XGBoost is:

$$Obj = \Sigma L(y_i, \hat{y}_i) + \Sigma \Omega(f_k)$$

where:
$L(y_i, \hat{y}_i)$= prediction loss function, $\Omega(f_k)$ = regularization term
y_i = actual class label, $\hat{y}_i$ = predicted class label
The objective function minimizes prediction error while controlling model complexity.

C. Disease Risk Probability

The probability generated by the selected prediction model is converted into a disease risk percentage as:
Risk (%) = P × 100
where:
P = disease probability score generated by the prediction model
The calculated value represents the likelihood of disease occurrence.

D. Risk Classification

The generated probability score is categorized into different risk levels as follows:
Low Risk: $P < 40\%$
Medium Risk: $40\% \leq P \leq 70\%$
High Risk: $P > 70\%$
The classification assists in identifying the severity of the predicted disease risk.

E. Final Output

The final output generated by the AyurCard prediction engine is represented as:
Output = {Disease, Risk, Severity, Insights}
where:
Disease= predicted disease, Risk = disease probability percentage
Severity= Low, Medium, or High risk level, Insights = graphical visualization and healthcare recommendations
The generated output supports disease risk assessment and clinical decision-making.

VII. Results and Discussion

A. Comparative Analysis of Prediction Models

Random Forest and XGBoost models were evaluated for disease risk prediction using healthcare records containing clinical parameters, symptoms, laboratory reports, and diagnosis history. Model performance was assessed using Accuracy, Precision, Recall, and F1-Score metrics. Comparative evaluation showed that XGBoost generated more refined disease risk predictions through its iterative error-correction mechanism, whereas Random Forest provided stable baseline performance through ensemble learning and majority voting. The results demonstrate the applicability of ensemble machine learning techniques for healthcare prediction tasks involving multiple clinical attributes [20].

B. Disease Risk Assessment and Prediction Outcomes

The prediction module generated probability scores for both chronic and acute disease risks using patient healthcare records. Historical medical records were utilized for chronic disease prediction, while recent clinical observations and symptom patterns were utilized for acute disease prediction [21]. The generated probability scores were categorized into Low, Medium, and High Risk levels, providing a structured approach for disease risk assessment and prediction interpretation.

C. Risk Visualization and Clinical Insights

Prediction outcomes were represented through probability-based visualizations, risk indicators, and severity classifications. The generated visual insights improved the interpretability of prediction results and supported healthcare professionals in assessing patient health conditions.
The risk visualization mechanism provided a clear representation of disease probability and severity levels, enabling data-driven clinical decision support [22].

D. System-Level Impact of AyurCard

The integration of Centralized Electronic Health Records (EHR) with AI-based disease prediction enhanced healthcare information management and clinical decision support.

The AyurCard-ID enabled unified access to patient healthcare records, while Role-Based Access Control (RBAC) ensured secure information sharing among patients, doctors, authorized medical stores, and administrators. The framework further supported healthcare coordination through digital prescription management, appointment tracking, and centralized medical record accessibility [23].

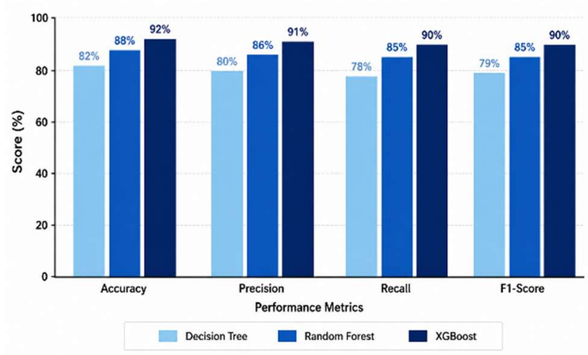

Fig. 3 Performance Comparison of Machine Learning Models

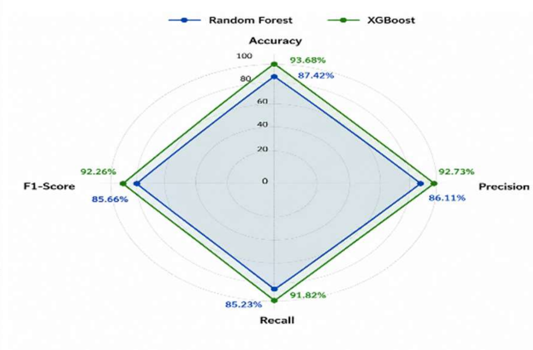

Fig. 4 Overall Model Comparison

E. Overall Discussion

The results demonstrate the feasibility of integrating centralized healthcare records, machine learning-based risk assessment, and healthcare management services within a unified healthcare platform. The combination of Electronic Health Records, predictive analytics, and secure healthcare access mechanisms improves healthcare information availability and clinical decision support. The proposed AyurCard framework establishes a foundation for AI-assisted healthcare management, disease risk assessment, and coordinated healthcare service delivery across multiple healthcare stakeholders [24] [25].

VIII. FUTURE SCOPE

- Aadhaar-Linked Digital Health Identity: Integration of AyurCard-ID with Aadhaar can enable secure authentication, unified patient identification, and seamless access to healthcare records across hospitals and healthcare services.
- AI-Based Doctor Recommendation System: Machine learning techniques can be utilized to recommend suitable doctors based on patient symptoms, diagnosis history, specialization requirements, and healthcare availability.
- IoT-Based Remote Health Monitoring: Integration with wearable devices and healthcare sensors can facilitate continuous monitoring of vital parameters and support real-time health assessment.
- Interoperable Healthcare Ecosystem: The framework can be integrated with hospitals, diagnostic centers, pharmacies, insurance providers, and government healthcare systems to enable secure healthcare data exchange and coordinated patient care.

IX. CONCLUSION

AyurCard is presented as an AI-enabled unified digital healthcare and intelligent medical system designed to address the limitations associated with fragmented healthcare infrastructures. The integration of centralized electronic health records with a unique digital identity, combined with AI-driven analytics, enhances diagnostic accuracy, supports preventive healthcare, and improves overall system efficiency. The system enables seamless interaction among patients, healthcare professionals, and administrative entities while ensuring data security, transparency, and controlled access.

Intelligent data analysis and predictive modeling facilitate early disease detection and personalized treatment planning, leading to improved patient outcomes and more informed clinical decision-making.

Despite existing challenges related to data security, interoperability, and infrastructure, the proposed framework provides a scalable foundation for the development of advanced healthcare solutions. With ongoing research and technological progress, the system holds strong potential to evolve into a comprehensive healthcare intelligence platform, supporting clinical operations, public health management, and sustainable healthcare development.

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