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An Intelligent Multi-Disease Diagnostic Framework using Machine Learning

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ABSTRACT: As non-communicable diseases (NCDs) like Diabetes and Cardiovascular conditions continue to dominate global mortality rates, the need for low-latency, high-accuracy screening tools becomes crit-ical. This paper presents a novel approach to medical diagnostics by integrating a Decoupled Microservices architecture with advanced Ensemble Learning. We implement an Adaptive Boosting (AdaBoost) model for metabolic screening and a Gradient Boosting Machine (GBM) for cardiovascular risk assessment. By utilizing a MERN (MongoDB, Express, React, Node.js) stack integrated with a dedicated Python analytical engine via RESTful APIs, the system achieves a significant reduction in diagnostic latency (150ms–250ms). Experimental results on UCI datasets demonstrate a peak accuracy of 86.5% for diabetes and 89.2% for heart disease. This research provides a comprehensive end-to-end framework for scalable clinical decision support systems (CDSS) designed for real-world deployment in underserved regions.

KEYWORDS: Healthcare Informatics, Ensemble Learning, AdaBoost, GBM, Microservices Architecture, MERN Stack, Clinical Decision Sup-port.

I. INTRODUCTION

THE integration of artificial intelligence into clinical workflows marks a paradigm shift from reactive to preventive medicine. In the contemporary medical land-scape of 2026, the bottleneck remains the early detection phase, where physiological changes often go unnoticed until clinical symptoms become severe.

- **Background and Significance**

Healthcare Informatics exists at the intersection of infor-mation science, computer science, and healthcare. Chronic diseases, particularly Diabetes and Cardiovascular Diseases, account for over 70% of global mortality. The complexity of these diseases involves multi-dimensional clinical biomark-ers (e.g., BMI, Glucose, Cholesterol, and Blood Pressure) that interact in non-linear ways. Traditional statistical models often fail to capture these intricate correlations, suffering from high bias or high variance.

- **Problem Statement**

Despite advancements, the current diagnostic landscape is hindered by systemic inefficiencies. First, diagnostic latency leaves a vast majority of the population without access to preventive healthcare. Second, traditional diagnostic meth-ods are fragmented, creating ”data silos” where informa-tion cannot flow seamlessly. Third, many existing tools act as ”black boxes,” offering no clinical transparency for the generated risk scores.

- **Research Contributions**

This paper provides the following technical contributions to the field of Healthcare Informatics:

- A high-availability microservices architecture that isolates heavy AI inference from the user-facing web server.
- A comparative analysis of sequential boosting learn-ers (AdaBoost and GBM) in a multi-disease con-text.
- A ”Single-Window” user interface design that sim-plifies the clinical assessment journey.
- Empirical validation of end-to-end system latency, proving the feasibility of real-time diagnostics.

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II. LITERATURE SURVEY AND RESEARCH GAP

To construct a scientifically valid CDSS, a comprehensive review of existing methodologies was conducted.

- **Machine Learning in Metabolic Screening**

Current literature highlights the limitations of standalone classifiers like SVM and Decision Trees in handling noisy clinical data. Research demonstrates that AdaBoost (Adap-tive Boosting) effectively synthesizes a ”strong learner” from decision stumps by focusing on misclassified sam-ples through adaptive weighting. This iterative weight-adjustment mechanism creates highly precise decision boundaries for metabolic markers.

- **Cardiovascular Risk and Gradient Descent**

For heart disease diagnosis, Gradient Boosting Machines (GBM) have shown superior performance. Unlike bagging methods that build trees in parallel, GBM builds trees se-quentially to predict the residual errors of prior models. This allows the algorithm to optimize a differentiable loss func-tion, effectively capturing complex interactions between age, chest pain type, and ST-segment depression.

- **The Architectural Research Gap**

While many studies focus on algorithm accuracy, very few address the deployment architecture. Most researchers pro-vide a local Python script; our research bridges the gap be-tween the model and the end-user by providing a scalable, full-stack microservices solution using the MERN stack.

III. THEORETICAL FRAMEWORK AND METHODOLOGY

The methodology harmonizes robust data science practices with a modern full-stack architecture.

- **Dataset Selection and Preprocessing**

The system utilizes gold-standard datasets from the UCI Machine Learning Repository.

Data Cleaning

Medical datasets frequently contain missing values, such as biologically impossible zero values for glucose. The system employs Mean and Median Imputation for continuous vari-ables and Mode Imputation for categorical attributes.

Normalization

To prevent features with larger ranges (e.g., Cholesterol) from dominating those with smaller ranges (e.g., BMI), Z-score standardization was applied:

$x - \mu$

A learning rate (shrinkage factor) is applied to prevent the model from converging too quickly and overfitting the training data.

3.2 GBM Logic for Cardiovascular Analysis

GBM minimizes a loss function $L(y, F(x))$ by adding new trees that follow the negative gradient. The updated model $F_m(x)$ at iteration m is:

$$F_m(x) = F_{m-1}(x) + \gamma_m \sum_{i=1}^{n} \frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} \quad (4)$$

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The system leverages a Decoupled Microservices Design, divided into three logical tiers.

- **The Presentation Layer (Frontend)**

The user interface is a Single Page Application (SPA) de-veloped using React.js. It handles the dynamic visualization of diagnostic reports and uses Axios for asynchronous API communication.

- **The Application Layer (Backend)**

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The Node.js and Express.js server acts as the API Gateway. It manages JSON Web Tokens (JWT) for secure authentication and routes clinical data payloads to the analytical engine.

- **The Analytical Layer (Microservice)**

A dedicated Python Flask microservice hosts the pre-trained AdaBoost and GBM models. The models are serialized using Pickle (.sav) files, enabling near-instant inference without the need for retraining on every request.

$z =$ (1)

σ

where x is the raw value, μ is the mean, and σ is the standard deviation.

4.4 AdaBoost Logic for Diabetes Prediction

AdaBoost constructs a ”strong learner” by iteratively refin-ing ”weak learners.” Let $D_t(i)$ be the weight of the i-th instance at step t. The error ϵ_t of the weak classifier h_t is calculated as:

$\epsilon_t = D_t(i)$ (2)

$i{:}ht(xi) \neq yi$

The algorithm calculates a weight α_t for each classifier based on its error rate:

(3)

$\alpha = \frac{1}{} \ln \frac{1-\epsilon_t}{}$

Instance weights are then updated so that misclassified samples receive higher importance in the next round.

Fig. 1. Single-column System Architecture: Demonstrating the RESTful communication between the React Client, Node.js Gateway, and Flask Inference Service.

V. DESIGN DIAGRAMS AND PROCESS FLOW

- **Logical Workflow**

When a user submits health data, it is validated on the client side before being transmitted as a JSON payload to the backend. The Python API receives the data, executes the corresponding model, and returns a prediction score and classification.

where TP is True Positives, TN is True Negatives, FP is False Positives, and FN is False Negatives. The F1-Score balances Precision and Recall:

$F1 = 2 \cdot \; Precision \cdot Recall$

$Precision + Recall$

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5.2 Performance Metrics Analysis

(6)

As detailed in Table 1, the GBM model achieved an accuracy of 89.2% and a recall of 87.0%. High recall is critical in a medical context to minimize False Negatives. The AdaBoost model provided highly stable output for metabolic risk assessment with an 86.5% accuracy.

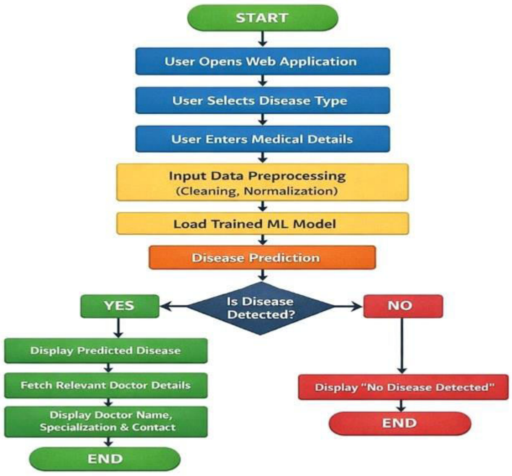

Fig. 2. Data Processing Pipeline: Step-by-step logic from input validation to result persistence.

TABLE 1
System Performance Comparison (UCI Datasets)

Metric	AdaBoost (Diabetes)	GBM (Heart)
Accuracy	86.5%	89.2%
Precision	84.2%	88.5%
Recall (Sensitivity)	82.1%	87.0%
F1-Score	83.1%	87.7%

- **Data Persistence and Schema**

MongoDB Atlas provides a NoSQL solution for storing diagnostic history. The Entity-Relationship structure links User profiles securely to their generated Medical Predic-tions.

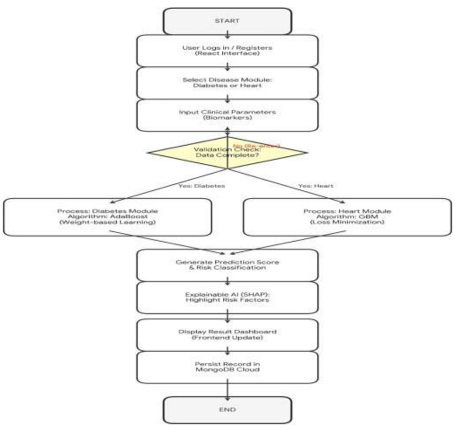

Fig. 3. Entity Relationship Diagram: Structure of MongoDB collections for patient tracking.

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VI. EXPERIMENTAL RESULTS AND DISCUSSION

The models were evaluated using a multi-dimensional suite of metrics to ensure clinical reliability.

- **Evaluation Metrics**

The primary metrics include Accuracy, Precision, Recall (Sensitivity), and the F1-Score. Accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

ROC-AUC 0.89 0.92

- **ROC-AUC Curve Analysis**

The Area Under the Curve (AUC) represents the model's ability to distinguish between classes. The GBM model achieved "Excellent Discrimination" with an AUC of 0.92, while AdaBoost maintained "Good Discrimination" at 0.89.

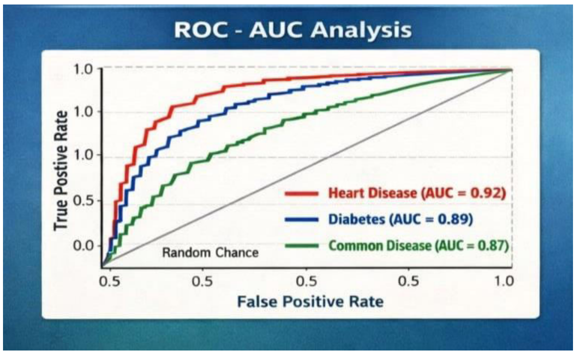


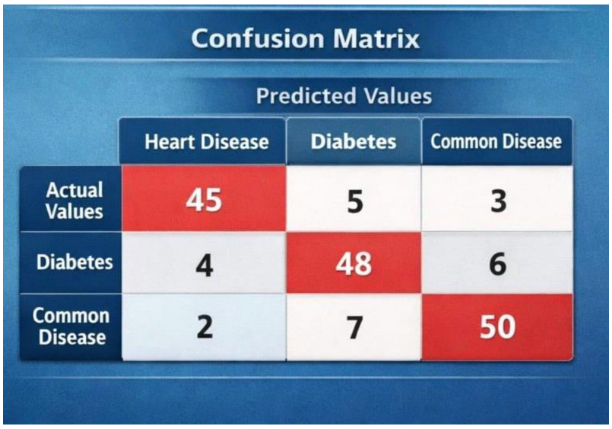
Fig. 4. ROC-AUC Curve analysis demonstrating the true positive rate vs false positive rate.

- **Latency Analysis and System Efficiency**

To validate the system's "Industry-Ready" status, latency was measured across three stages:

- **API Gateway Processing:** 50ms–100ms.
- **Machine Learning Inference:** 15ms–30ms.
- **Total End-to-End Latency:** 150ms–250ms.

By offloading mathematical computations to the Python mi-croservice, the main web server is never blocked, allowing for concurrent user scaling.



	Heart Disease	Diabetes	Common Disease
Actual Values	45	5	3
Diabetes	4	48	6
Common Disease	2	7	50

Fig. 5. Confusion Matrix analysis indicating the minimization of False Negatives in the ensemble models.

- **Explainable AI (XAI) Integration**

To address the ”black box” nature of boosting algorithms, the system integrates SHAP (SHapley Additive exPlana-tions). This provides clinical transparency by highlighting the specific biomarkers (e.g., high glucose) that pushed the model toward a diagnosis.

VII. CONCLUSION AND FUTURE SCOPE

7.1 Summary of Contributions

The proposed Intelligent Multi-Disease Prediction System successfully demonstrates the viability of integrating advanced ensemble machine learning models within a decou-pled, highly scalable microservices web architecture. The integration of the MERN stack with a dedicated Python Flask analytical engine allowed the system to achieve an end-to-end inference latency of 150ms to 250ms, proving its efficacy for high-traffic environments.

- **Clinical Efficacy**

Clinically, the deployment of sequential boosting algorithms yielded superior diagnostic metrics. The GBM model minimized the rate of False Negatives, and the AdaBoost model achieved robust metabolic screening. These metrics confirm that focusing on iterative error correction in ”hard-to-classify” patient profiles significantly enhances the reliability of Clinical Decision Support Systems (CDSS).

- **Future Work and Research Directions**

Future iterations will focus on continuous, dynamic health monitoring:

- *IoT and Wearable Integration:* Integrating real-time data streams from IoT devices to capture temporal physiological fluctuations.
- *Federated Learning:* Employing Federated Learning to train models across distributed hospital networks without centralizing sensitive patient records.
- *Expansion of Disease Modules:* Scaling the infer-ence microservice to include predictive models for Chronic Kidney Disease and Hepatic anomalies.

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