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CM Health Care: An Intelligent Full-Stack AI Framework for Pima Indian Diabetes Prediction and Automated Clinical Report Generation

Bibhuti Bhusan Swain
Department of Master of Computer Applications
GIFT Autonomous, Bhubaneswar, Odisha, India, bswain2024@gift.edu.in

Sambit Lenka
Department of Master of Computer Applications
GIFT Autonomous, Bhubaneswar, Odisha, India, sambitlenka2024@gift.edu.in

Allupati Chakradhar Patro
Assistant Professor(Master of Computer Applications)
GIFT Autonomous,Bhubaneswar, Odisha, India, allupati@gift.edu.in

Abstract—Diabetes Mellitus remains one of the fastest-growing global metabolic disorders, leading to severe multi-organ long-term failure if undetected. Early diagnostic classification serves as a crucial mechanism for patient risk mitigation. This paper presents 'CM Health Care', a comprehensive, production-grade cloud- integrated AI framework that closes the loop between algorithmic predictive accuracy and actual clinical workflow deployment. Utilizing the Pima Indian Diabetes Dataset, we implement a highly optimized Logistic Regression engine utilizing automated feature imputation via custom-calculated localized central tendencies. The core statistical engine achieves a benchmark classification accuracy of 75.97% with highly stable generalized gradients. To bridge the gap between machine intelligence and practical medical utilization, we design a state-of-the-art

dual-portal Streamlit ecosystem supporting asynchronous secure Multi-Factor Authentication via automated SMTP One-Time Password tokens. The platform accommodates customized clinical dashboards for physicians, full patient risk profiling pipelines, and dynamically generated PDF prognostic health reports. This study details the end-to-end framework from statistical preprocessing through to production-ready database management, demonstrating a highly reproducible template for intelligent modern health informatics networks.

- Keywords—Diabetes Mellitus, Logistic Regression, Streamlit Architecture, SMTP Protocol, Automated Health Reports, Clinical Dashboards, Database Persistence.

I. INTRODUCTION

The contemporary transformation of healthcare informatics is heavily anchored on the inclusion of intelligent decision support mechanisms. Metabolic syndromes, particularly Diabetes Mellitus, represent an epidemiological challenge due to their silent progression patterns. Early diagnostic classification enables clinical practitioners to formulate preventative interventions before physiological damage becomes irreversible.

While standard machine learning algorithms have demonstrated significant success in high-fidelity academic environments, their translation to concrete clinical workflows is frequently restricted by a lack of secure, intuitive operational infrastructures. Most existing systems operate as isolated offline models, requiring data scientists to manually input records and parse raw matrix predictions. This creates an un-scalable operational chasm between raw mathematical performance and dynamic patient care execution.

To directly address this gap, this paper introduces the **CM Health Care Framework**, an integrated predictive full-stack ecosystem. The underlying architecture encapsulates custom mathematical preprocessing, highly generalized linear classification, a robust relational data vault, secure asynchronous user state validation, and programmatic generation of legally structures medical records.

II. LITERATURE REVIEW

Automated diabetic screening has experienced an evolution from rule-based expert engines to modern high- dimensional neural representations. Traditional architectures heavily leveraged deep deep-learning models, which often suffer from extreme overfitting on small clinical cohorts and exhibit low transparency, rendering them problematic for direct clinical deployment where algorithmic audibility is paramount.

III. METHODOLOGY

A. Dataset Profile and Statistical Features

The analytical validation of the framework is conducted using the Pima Indian Diabetes Dataset originating from the National Institute of Diabetes and Digestive and Kidney Diseases. The dataset captures a total of 768 clinical observations across 8 explicit biological covariates and 1 binary categorical objective variable representing diabetic status.

The input features comprise:

- **Pregnancies:** Quantified gestations.
- **Glucose:** 2-hour plasma glucose concentration.
- **BloodPressure:** Diastolic measurement (mm Hg).
- **SkinThickness:** Triceps skin fold (mm).
- **Insulin:** 2-hour serum insulin (μU/ml).
- **BMI:** Body mass index (weight in kg/(height in m)^2).
- **DiabetesPedigreeFunction:** Genetic score.
- **Age:** Calendar duration in years.

B. Advanced Statistical Preprocessing

An empirical inspection of the feature matrix reveals extensive invalid physiological null values coded as literal zero elements. For instance, an insulin concentration or a blood pressure reading of absolute zero represents biological invalidity. To prevent dangerous model distortion without dropping valuable data rows, a hybrid imputation strategy was engineered.

For highly skewed features, specifically serum ***Insulin***, the invalid zeroes are systematically replaced by the mathematical mean of the valid feature space. For the remaining covariates, a median-imputation model is executed to ensure outlier protection. The transformation maps as follows:

$$X_{Insulin} = \{ x \in X : x \neq 0 \} \rightarrow \mu$$

Recent literature highlights that for datasets such as the Pima Indian Diabetes cohort, structured linear formulations with L2 regularization behave as superior models because they resist feature noise while providing high structural explicability through explicit log-odds coefficients. Research by Smith et al. demonstrated that random data missingness, often captured as zero-values in biological indicators such as insulin and glucose, heavily skews algorithmic decisions if dropped indiscriminately. Consequently, advanced statistical imputation combined with robust multi-tenant authentication layers forms the logical baseline for enterprise deployment strategies.

$$x_i = 0 \Rightarrow x_i = \mu_{Insulin}$$

C. Mathematical Modeling & Logistic Regression

The classification engine leverages a regularized multi- variable Logistic Regression model initialized with an L2 penalty constraint to prevent parameter divergence. The system establishes a linear decision boundary mapped to a probability space via the transcendental sigmoid operator.

The formal hypothesis function is defined by:

$$h_\theta(x) = \sigma(\theta^T x) = 1 / (1 + e^{-\theta^T x})$$

where the linear transformation layer corresponds to:

$$\theta^T x = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

The loss function optimized during gradient iteration is the standard binary cross-entropy loss augmented with an L2 ridge regularization factor to guarantee parameter shrinkage:

$$J(\theta) = -\left[(1/m) \Sigma \left(y^{(i)} \log(h_\theta(x^{(i)})) + (1-y^{(i)}) \log(1- h_\theta(x^{(i)}))\right)\right] + (\lambda/2m) \Sigma \theta^2$$

The optimization solver is set to the Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) algorithm with a maximum iteration threshold of 250 cycles, ensuring complete numerical alignment and stable log- likelihood maximization.

IV. EXPERIMENTAL RESULTS

A. Model Evaluation and Performance Metrics

The processed dataset was partitioned into an 80% operational training slice and a 20% strictly isolated test matrix to provide cross-validation security. Upon model compilation, the binary target vector classification output generated highly stable diagnostic parameters.

The mathematical evaluation demonstrates a global classification accuracy score of exactly **75.97%** on the unseen test matrix. This represents a highly generalized baseline that minimizes variance, ensuring that when deployed inside a live hospital clinic environment, the system remains immune to volatile diagnostic predictions.

TABLE I: CONFUSION MATRIX MATRIX DISTRIBUTION

The analytical derivations of standard clinical efficiency indices are formalized below:

- **Precision:** Measures the fidelity of positive diagnostic flags, computed via ***TP / (TP + FP)***, yielding a score of 66.67%.
- **Recall (Sensitivity):** Represents the system's capacity to intercept active diabetic patients, computed via ***TP / (TP + FN)***, yielding a score of 65.45%.
- **F1-Score:** The harmonic balance between precision and sensitivity, defined as ***2 × (P × R) / (P + R)***, yielding 66.05%.

TABLE II: PERFORMANCE INDEX SUMMARY

Evaluation Parameter	**Numerical Value (%)**
Global Testing Accuracy	75.97 %
Statistical Precision	66.67 %
Empirical Recall / Sensitivity	65.45 %
Balanced F1-Score	66.05 %

Clinical Interpretation of Coefficients

The mathematical weights derived by the L-BFGS solver expose the structural impact of individual biometric variables on the probability of diabetes onset. The feature ***Glucose*** acts as the dominant positive driver of log-odds variations, closely followed by ***BMI*** and ***Pregnancies***.

Conversely, features such as ***BloodPressure*** demonstrate stable, non-volatile distribution mapping, showing that regularized linear modeling aligns perfectly with traditional empirical metabolic studies.

Actual \ Predicted	Predicted Negative (0)	Predicted Positive (1)
Actual Negative (0)	81 (True Neg)	18 (False Pos)
Actual Positive (1)	19 (False Neg)	36 (True Pos)

```
===MODELLOGISTICWEIGHTEXTRACT===
Feature:Glucose                 ->Weight:
+0.035
Feature:BMI                     ->Weight:
+0.082
Feature:Pregnancies             ->Weight:
+0.064
Feature:Age                     ->Weight:
+0.012
ModelBias(Intercept)            ->Value:
-8.421
SolverConvergenceStatus         ->Success
(250 Iterations)
```

V. FULL-STACK SYSTEM ARCHITECTURE

A. Streamlit Multi-Page Framework

The user facing software architecture is built as a reactive, multi-page application using the Streamlit framework. Rather than relying on traditional multi-file routing which suffers from heavy page load latency, the application manages multi-page routing dynamically via an atomic execution state variable (***st.session_state.page***).

The global system router processes five distinct page states, executing deterministic conditional switching rules:

- **Welcome State:** The root landing page displaying branding, operational stats, and primary navigation hooks.
- **Login Selection State:** A critical authorization bifurcation layer routing to separate doctor and patient validation gates.
- **Doctor Login / Portal:** Secure management dashboard executing localized biometric querying.
- **Patient Portal:** Gateway providing explicit self- service access to historical diagnosis tracking.
- **Prediction Engine Interface:** The core data-entry view utilizing localized form validation blocks.

B. Asynchronous SMTP MFA Token Engine

To comply with rigorous health information data security standards, a customized multi-factor authentication (MFA) system was engineered directly into the core runtime environment utilizing the Simple Mail Transfer Protocol (SMTP) with native Secure Sockets Layer (SSL) encryption on port 465.

When a professional user triggers a login transaction, the system initiates an asynchronous cryptographic generator that builds a 6-digit absolute random numeric string. The token is mapped instantly to the session variable while an active worker thread dispatches an encrypted email package via ***smtp.gmail.com***.

The transaction cannot proceed until the system matches user input with the server-side generated string, preventing unauthorized baseline script injections into patient database tables.

TABLE III: CORE APPLICATION SECURITY ROLES

Role Node	**Access Boundary**	**Auth Layer**
Anonymous	Landing Page / Metrics Only	None
Patient	Personal Diagnostic History	Standard DB Query
Medical Dr.	Global Diagnostics, Prediction Node	Asynchronous SMTP MFA

C. Relational Database Architecture & Persistence

State persistence across user runtime instances is managed by an integrated SQLite database architecture backend. The system abstracts physical writes through explicit Structured Query Language parameters executed via the Python native database driver interface.

The primary structural repository is defined as the ***patients*** schema, containing explicit variable constraints. Every transaction generated from the predictive portal is saved sequentially with structural time-stamps, ensuring historical tracking and legal auditing compliance for clinicians.

The utilization of structural type mapping restricts malicious input buffer attacks and prevents application runtime failures due to mismatched input types.

D. Programmatic Medical PDF Report Engine

A critical novelty within the 'CM Health Care' ecosystem is the deployment of an automatic programmatic clinical report writer. Upon completion of a prediction request, the system processes raw diagnostic classifications and transforms them into an official document format using a custom HTML canvas compilation layer converted directly via binary page media layout models.

The generated asset incorporates critical parameters required by medical regulatory bodies, containing explicit patient demographics, precise model confidence probabilities, standardized risk assessments, and placeholder boundaries for authentic signatures. This document architecture provides patients with immediate portable physical validation of their clinical screenings.

VI. SYSTEMATIC OUTPUT VERIFICATION

A. Analytical Evaluation of Specific Dashboard Interfaces

To verify the practical implementation of the platform, exhaustive black-box validation of every structural node was conducted. The specific outputs generated by each view are documented as follows:

1) Welcome / Root Screen: Generates a high-fidelity visual summary of clinic efficiency metrics. It renders real-time tracking elements including total consultations, historical patient volume counters, and live analytics distributions across major internal departments (e.g., Gastrointestinal, Endocrine, and Diabetes units) using responsive vector chart instances.

2) Authentication Interface Screen: Presents responsive input blocks requesting

```
--DATABASESCHEMAPROFILE--
CREATETABLEpatients(
    idINTEGERPRIMARYKEYAUTOINCREMENT, name
    TEXT NOT NULL,
    pregnanciesINTEGER,
    glucose REAL,
    blood_pressureREAL,
    skin_thicknessREAL,
    insulin REAL,
    bmi REAL,
    pedigreeREAL,
    age INTEGER,
    prediction_label TEXT,
    confidence_score REAL,
    timestampDATETIMEDEFAULT
CURRENT_TIMESTAMP
);
```

destination parameters. When verified, the screen shifts state to display a secure token entry widget, providing interactive text-feedback notifications regarding verification successes or credential mismatches.

3) Diagnostic Prediction Control Panel: Features a structured data entry form containing custom constraints matching biological parameters (e.g., locking input selectors within safe physiological bounds, such as a BMI range between 10 and 70).

Upon clicking the "Evaluate Clinical Risk" action handler, the underlying system executes instant matrix multiplication against the regularized weights stored inside the binary model file (***model_logistic.pkl***). The system computes exact classification ratios and displays interactive alert boxes on screen.

Historical Ledger View: Renders a dynamic data table summarizing all transactions stored within the SQLite layer. Physicians can inspect patient parameters, filter entries, or click a button to re-generate copies of historical health reports instantly.

TABLE IV: ANALYTICAL INTERFACE VERIFICATION SUMMARY

Page UI View	Functional Component Verified	Status
Welcome Page	Departmental Analytics & Volume Plots	Active
Login Hub	Dynamic Session State Switching	Active
MFA Security	Asynchronous SSL SMTP Token Loop	Active
Predictive Panel	joblib Linear Model Inference Engine	Active
Report Node	Automated PDF Report Compiler	Active

```
===REAL-TIMERUNTIMELOGOUTPUT===
[INFO]UserSessionInitiated:WelcomePortal [AUTH]
Triggering Asynchronous MFA for
user:doctor@cmhealth.org
[SMTP]Connectionestablishedtosmtp.gmail.com:465
[SMTP]SecureMFATokentransmittedsuccessfully.
[DB]Connectioninitializedfor'database.db'
[MODEL] Loading serialized joblib object...
Success.
[ENGINE]Inputsparsed:Glucose=148,BMI=33.6,
Age=50
[ENGINE]ComputedProb:0.8415->Label:HighRisk
[DB]Transactionwrittensuccessfully.ID:1042
[PDF]ProgrammaticReportCompiled.Output:
_report.pdf
```

VII. DISCUSSION

The empirical performance of the system highlights significant design advantages. Achieving a generalized testing accuracy of 75.97% using a simple linear mechanism provides clear computational and structural interpretability benefits over un-auditable deep deep- learning networks. In high-stakes medical informatics, knowing exactly how a model reaches a prediction is essential for clinical adoption.

Furthermore, evaluating the system's runtime framework proves that integration bottlenecks can be resolved without complex enterprise cloud architectures. Utilizing localized data persistence via an SQLite backend ensures complete isolation, low processing latency, and high scalability for small to mid-sized regional medical centers.

The implementation of an automated Multi-Factor Authentication (MFA) system directly addresses data privacy regulations by introducing a robust barrier against unauthorized network interactions. Programmatically generating medical records also saves considerable administrative time, allowing clinical teams to focus directly on patient interventions rather than manually documenting diagnostic data files.

VIII. CONCLUSION & FUTURE SCOPE

This study presented 'CM Health Care', a fully realized end-to-end clinical framework combining optimized machine learning with complete web application features. By addressing critical data challenges through localized median and mean imputation models, the regularized linear engine guarantees highly dependable risk stratification metrics. The surrounding system architecture successfully solves typical application security, database persistence, and automated medical reporting needs.

Future development will focus on incorporating advanced ensemble architectures, including Gradient Boosting Machines and Random Forests, while maintaining feature interpretability using SHAP (Shapley Additive exPlanations) values. Additionally, expanding the local database architecture to sync with HL7/FHIR compliant distributed healthcare networks will facilitate international enterprise hospital interoperability.

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