**Phase-1 Submission**

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**Institution:** Dhanalakshmi college of engineering

**Department:** Computer Science and Engineering

**Date of Submission:** 30-04-2025

# 1.Problem Statement

**AI – POWERED DISEASE PREDICTION**

Transforming healthcare with AI-powered disease prediction based on patient data.

**2.Objectives of the Project**

**Project Objective:**

To develop an AI-powered system that predicts the risk of diseases using patient data, enabling early diagnosis, personalized care, and better clinical outcomes.

**Key Outcomes:**

* Train machine learning models to predict diseases based on patient demographics, medical history, and lifestyle factors.
* Classify patients into risk categories for targeted intervention.
* Identify key predictors influencing disease risk.
* Evaluate model accuracy using metrics like precision, recall, and AUC.
* Provide a decision-support tool for clinicians with risk insights and recommendations.

# 3.Scope of the Project

**Features to Analyse/Build:**

1. **Demographics:**
   * Age, gender, ethnicity, location
2. **Medical History:**
   * Past diagnoses, family history of diseases, previous hospitalizations
3. **Vital Signs & Clinical Metrics:**
   * Blood pressure, heart rate, BMI, cholesterol, glucose levels
4. **Lab Test Results:**
   * Blood work, urinalysis, liver/kidney function tests
5. **Lifestyle Factors:**
   * Smoking status, alcohol consumption, physical activity, diet
6. **Medication & Treatment History:**
   * Current/past prescriptions, treatment adherence
7. **Genetic or Genomic Data (if available)**
8. **Time-Series Data (for longitudinal analysis):**
   * Trends in vitals or lab values over time

**Limitations & Constraints:**

1. **Data Constraints:**
   * Use of publicly available or anonymized datasets (e.g., MIMIC-III, UCI Health datasets)
   * Missing or imbalanced data may affect model performance
2. **Model Constraints:**
   * Limited to interpretable models if required by clinical partners (e.g., logistic regression, decision trees)
   * Avoid black-box models unless explainability techniques (e.g., SHAP, LIME) are applied
3. **Deployment Constraints:**
   * Prototype may not be deployed in real clinical settings without regulatory approval (e.g., FDA clearance)
   * Compliance with data privacy laws (e.g., HIPAA, GDPR)
4. **Tool Constraints:**
   * Development limited to Python-based frameworks (e.g., scikit-learn, TensorFlow, PyTorch)
   * Visualization using tools like Streamlit, Dash, or Power BI

# 4.Data Sources

**Dataset Description:**

|  |  |  |
| --- | --- | --- |
| • | **Dataset Name** : | Healthcare Dataset |
| • | **Source** : | Kaggle ([dataset](https://www.kaggle.com/datasets/mathchi/diabetes-data-set)) |
| • | **Accessibility** : | Public |
| • | **Type** : | Static |

# 5.High-Level Methodology

* ***Data Collection*** – The dataset will be obtained through direct download from publicly available source **Kaggle** for disease diagnosis.

* ***Data Cleaning*** – Identify potential issues such as **missing values, duplicates,** or **inconsistent formats.**

* ***Exploratory Data Analysis (EDA)*** –

**Predictive Modeling & Risk Analysis** • **Techniques:**

* 1. **Logistic regression, decision trees, or random forests** – for predicting disease risk.
  2. **Survival analysis (e.g., Kaplan-Meier curves)** – for analysing time to event (e.g., time until readmission).

• **Visualizations:**

* 1. **ROC curves / AUC plots** – to evaluate model performance.
  2. **Survival curves** – to compare patient outcomes by treatment groups.

* ***Model Building***:

**Supervised Learning**

1. **Logistic Regression** – Simple, interpretable, great for binary outcomes.
2. **Random Forest** – Handles non-linear data, robust to noise.
3. **XGBoost/LightGBM** – High accuracy, handles complex patterns well.
4. **SVM** – Good for high-dimensional classification.
5. **Neural Networks** – Flexible, good for large and complex datasets.

**Unsupervised Learning**

1. **K-Means** – Fast and effective for patient clustering.
2. **Hierarchical Clustering** – Useful for exploring group hierarchies.

**Deep Learning (for Images/Text)**

**CNNs** – Best for medical image analysis.

**Transformers (e.g., BERT)** – Exellent for clinical text mining.

● ***Model Evaluation***

**Metrics**

1. **Classification:** Accuracy, Precision, Recall, F1 Score, ROC-AUC
2. **Regression:** MAE, RMSE, R²
3. **Survival:** C-index, Log-rank Test
4. **Clustering:** Silhouette Score, Clinical relevance

**Validation Strategies**

1. **Train-Test Split** – Simple, quick check
2. **k-Fold CV / Stratified k-Fold** – Robust, keeps class balance
3. **Time Series Split** – For time-dependent data
4. **Bootstrapping** – Good for uncertainty estimation

● ***Visualization & Interpretation***

**Visualization & Interpretation**

1. **Charts:** Line, bar, scatter, boxplots, heatmaps
2. **Dashboards:** Interactive summaries (e.g., Power BI, Tableau)
3. **Model Explainers:** SHAP, LIME, feature importance
4. **Reports:** Clear visuals + insights for stakeholders

# 6.Tools and Technologies

* **Programming Language** – The main language we use is Python.
* **Notebook/IDE** –The platform we use is Google Colob.
* **Libraries** – The libraries we use is pandas, NumPy, seaborn, matplotlib.

# 7.Team Members and Roles

|  |  |  |
| --- | --- | --- |
| **S.No** | **NAME** | **ROLE** |
| **1** | Agnes Selestina S | Data Collection*,* Data Cleaning |
| **2** | Christina Ryka S | Visualization & Interpretation |
| **3** | JeevikasriR | Exploratory Data Analysis (EDA), Feature Engineering |
| **4** | Keerthana R | ModelBuilding*,* ModelEvaluation |