Phase-1 Submission

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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
- **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 analyzing 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**

6. **K-Means** – Fast and effective for patient clustering.
7. **Hierarchical Clustering** – Useful for exploring group hierarchies.
8. **PCA** – Reduces dimensionality, reveals hidden patterns.

⏳ **Survival Analysis**

9. **Kaplan-Meier** – Estimates survival over time.
10. **Cox Model** – Assesses impact of risk factors on outcomes.

🧠**Deep Learning (for Images/Text)**

11. **CNNs** – Best for medical image analysis.
12. **Transformers (e.g., BERT)** – Excellent for clinical text mining.

- **Model Evaluation** –

  ✅ **Metrics**

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

   🔁 **Validation Strategies**

5. **Train-Test Split** – Simple, quick check
6. **k-Fold CV / Stratified k-Fold** – Robust, keeps class balance
7. **Time Series Split** – For time-dependent data
8. **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	Jeevikasri R	Exploratory Data Analysis (EDA), Feature Engineering
4	Keerthana R	Model Building, Model Evaluation