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1. Introduction

a. Project Overview

AnemiaSense is a machine learning-based web application developed to detect anemia using essential clinical parameters. It enables real-time prediction through a simple, user-friendly Flask web interface, making it a useful tool for early detection and management support.

b. Objectives

- i. Build a predictive model for anemia detection using machine learning.
- ii. Develop a web-based interface to collect patient data and display results.
- iii. Ensure the system is efficient, accurate, and easy to use for both medical and non-medical users.

2. Project Initialization and Planning Phase

a. Define Problem Statement

Anemia, a condition marked by low hemoglobin levels, often goes undetected until symptoms worsen. Manual detection can be slow and inconsistent. This project aims to automate and improve the accuracy of anemia detection using clinical data and machine learning.

b. Project Proposal (Proposed Solution)

Develop an ML model that predicts whether a patient is anemic based on health metrics. This model will be deployed through a Flask web application to allow instant predictions.

C. Initial Project Planning

- i. Select relevant clinical dataset
- ii. Preprocess and clean data
- iii. Train and evaluate multiple models
- iv. Deploy the best-performing model
- v. Build a responsive web UI

3. Data Collection and Preprocessing Phase

a. Data Collection Plan and Raw Data Sources Identified

Dataset sourced from a publicly available medical database containing features such as age, hemoglobin, hematocrit, MCV, MCH, MCHC, RBC count, and serum ferritin.

b. Data Quality Report

- i. Checked for missing values
- ii. Handled outliers using statistical methods
- iii. Normalized continuous values where needed
- iv. Encoded categorical labels

C. Data Exploration and Preprocessing

- i. Used Pandas and Seaborn for EDA
- ii. Found strong correlation between anemia and hemoglobin/RBC count
- iii. Applied standard scaling and label encoding
- iv. Split data into training and test sets (80:20)

4. Model Development Phase

a. Feature Selection Report

Selected features based on correlation and medical relevance:

-Age, Hemoglobin, Hematocrit, MCV,MCH, MCHC, RBC Count, Serum Ferritin

b. Model Selection Report

Trained and evaluated the following models:

- i. Decision Tree Classifier
- ii. Random Forest
- iii. Logistic Regression

Decision Tree was selected due to its simplicity, speed, and strong accuracy.

c. Initial Model Training Code, Model Validation and Evaluation Report

- i. Trained models using scikit-learn
- ii. Evaluated using accuracy, precision, recall, and F1 score
- iii. Decision Tree accuracy: -92%

5. Model Optimization and Tuning Phase

a. Hyperparameter Tuning Documentation

Performed GridSearchCV on:

- i. Max depth
- ii. Min samples split
- iii. Criterion (gini vs entropy)

b. Performance Metrics Comparison Report

Model | Accuracy | F1 Score | Precision | Recall

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Decision Tree | 92% | 0.91 | 0.90 | 0.93

Random Forest | 94% | 0.93 | 0.92 | 0.94

Logistic Regression | 88% | 0.86 | 0.84 | 0.88

c. Final Model Selection Justification

Decision Tree chosen for its balance of performance, interpretability, and low latency, ideal for real-time predictions in the web app.

6. Results

a. Output Screenshots

(Screenshots of the running web app displaying prediction results can be inserted here)

7. Advantages & Disadvantages

Advantages

1. Fast, accurate prediction
2. Simple UI for non-technical users
3. Deployable on any system with Python

Disadvantages

4. Model accuracy depends on data quality
5. Doesn't yet support multi-class classification or severity grading

8. Conclusion

AnemiaSense successfully demonstrates how machine learning can aid in the early diagnosis of anemia. It bridges the gap between medical data and actionable insights through an intuitive interface.

9. Future Scope

1. Expand model to classify anemia severity
2. Integrate more clinical features (e.g., iron levels, vitamin B12)
3. Add multilingual support for broader accessibility
4. Deploy to cloud platforms (Render, Heroku, etc.)