Multi-Modal Medical Risk Classifier

# Objective

The objective of this project is to develop a machine learning model that can predict a patient's medical risk level by analyzing two types of data: textual data from prescriptions and numerical lab results. The goal is to support early risk detection and assist in clinical decision-making.

# Tools & Technologies

- Python  
- PyTorch  
- Transformers (HuggingFace BERT)  
- Microsoft Word (.docx) for prescriptions  
- JSON for lab reports

# Methodology

1. Extract text from prescription files (.docx).  
2. Load key lab test results from structured JSON files.  
3. Use a pre-trained BERT model to extract embeddings from the prescription text.  
4. Combine text embeddings and lab values into a unified neural network model.  
5. Train the model using labeled data and evaluate its accuracy.  
6. Predict medical risk (Low or High) for new data.

# Dataset Description

The dataset includes simulated entries containing:  
- A .docx file with medical notes or prescriptions.  
- A .json file containing lab results such as HbA1c, Fasting Blood Sugar, Postprandial Blood Sugar, and Creatinine.  
- A binary label indicating the patient's risk level (0 = Low Risk, 1 = High Risk).

# Model Architecture

The model consists of:  
- A text projection layer for the 768-dimensional BERT embedding.  
- A lab projection layer for the 4-dimensional lab vector.  
- A classifier that combines both features and passes them through ReLU layers followed by a binary output layer.

# Training & Evaluation

The model is trained using CrossEntropyLoss and the Adam optimizer. Training is performed over multiple epochs on a small simulated dataset. The training loop tracks loss and evaluates accuracy after each epoch.

# Results

After training, the model can predict the medical risk category for new patient data. It outputs a label (Low or High Risk) along with the corresponding prediction probabilities.

# Conclusion

This project demonstrates how combining text and numerical data can improve clinical predictions. It serves as a foundation for building real-world tools that assist doctors by providing early warnings based on multimodal patient data.