Lab 4: Software Architecture Style

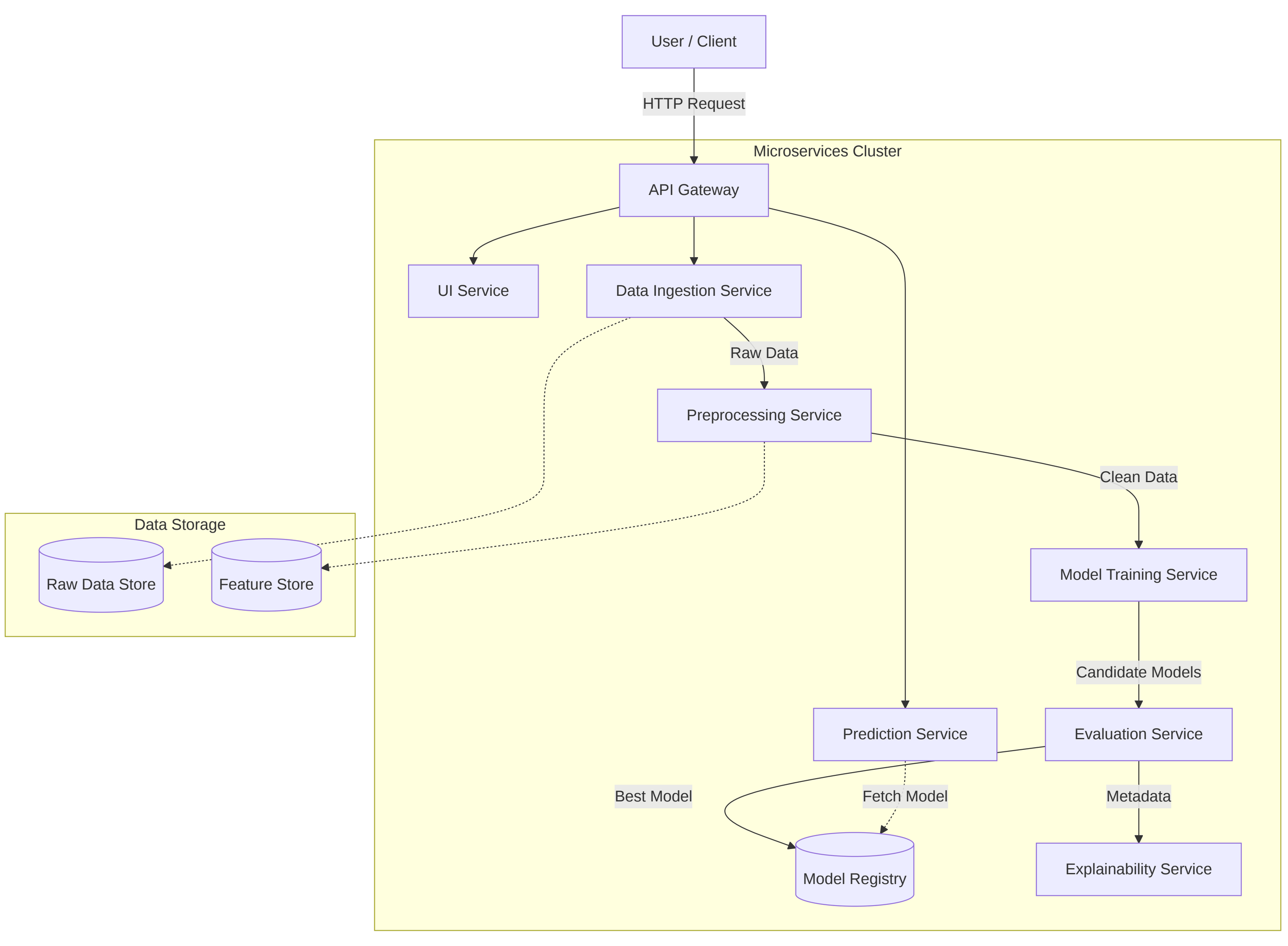
I. Chosen Architecture Style: Microservices Architecture

For the **AutoML Platform for Model Selection and Training**, the **Microservices Architecture** is the most appropriate choice. This style structures the application as a collection of loosely coupled services, which is ideal for the distinct and independent functionalities of an AutoML system.

A. Justification by Granularity of Software Components

The AutoML platform can be naturally decomposed into fine-grained, independent services, each responsible for a specific domain of the machine learning workflow.

- **User Interface (UI) Service**: Handles user interactions, dashboard rendering, and file uploads. It communicates with backend services via API gateways.
- **Data Ingestion Service**: Responsible for receiving raw datasets, validating formats (CSV, Excel), and storing them in a raw data storage (e.g., S3 or a database).
- **Data Preprocessing Service**: Cleans data, handles missing values, encodes categorical variables, and normalizes features. This service is compute-intensive and operates independently of the UI.
- **Model Training Service**: The core engine that trains multiple algorithms (Regression, Random Forest, etc.) in parallel. It uses the preprocessed data to generate candidate models.
- **Model Evaluation Service**: Tests the trained models against validation datasets using metrics like RMSE, Accuracy, etc., and selects the best-performing model.
- **Prediction Service**: Exposes the best model to generate predictions for new input data. It needs to be highly available and low-latency.
- **Explainability Service**: specialized service that analyzes the model to provide feature importance and decision explanations.



B. Justification for Best Choice

Microservices Architecture is the best choice for this project due to the following reasons:

- **Scalability:**
  - Different components of an AutoML system have vastly different resource needs. The **Model Training Service** is CPU/GPU intensive and may need to scale up significantly during training jobs, whereas the **UI Service** is lightweight.
  - Microservices allow us to scale *only* the training service (e.g., adding more worker nodes) without scaling the entire application, optimizing resource usage and cost.
- **Maintainability:**
  - The project involves distinct domains (data processing, ML algorithms, web UI). Separate teams or developers can work on the **Preprocessing Service** (using Python/Pandas) without affecting the **UI Service** (using React/Node.js).
  - Fault isolation ensures that if the *Training Service* crashes due to a memory error, the *UI* and *Prediction Service* remain operational.
- **Performance:**
  - Long-running tasks like model training can be processed asynchronously without blocking the user interface.
  - The **Prediction Service** can be optimized for low latency (e.g., using C++ or optimized inference runtimes) independent of the training logic.
- **Technology Heterogeneity:**
  - ML components are best written in **Python** (scikit-learn, TensorFlow), while the web backend might be better suited for **Node.js** or **Go**. Microservices allow each component to use the best tool for the job.

II. Application Components

The software engineering project consists of the following key application components:

1. Frontend (Web Application)

- **Description:** A responsive web interface built using **React.js** or **Vue.js**.
- **Responsibility:**
  - Allows users to upload datasets (CSV/Excel).
  - Provides a dashboard for selecting target variables and viewing model training progress.
  - Visualizes predictions and explainability reports (charts, graphs).
  - Communicates with the backend via REST APIs.

2. API Gateway

- **Description:** The entry point for all client requests, acting as a reverse proxy (e.g., **NGINX**, **Kong**).
- **Responsibility:**
  - Routes requests to appropriate microservices.
  - Handles authentication and rate limiting.
  - Aggregates responses from multiple services to reduce round-trips.

3. Backend Services (Microservices)

These are the core independent services implementing the business logic:

- **Data Ingestion Service**: Validates and stores raw uploaded files.
- **Preprocessing Service**: Performs data cleaning, imputation, and feature scaling.
- **AutoML Engine (Training Service)**: Orchestrates model selection and hyperparameter tuning. It spawns worker processes to train models like Linear Regression, Random Forest, and XGBoost.
- **Evaluation Service**: Computes metrics (RMSE, MAE, R2 for regression; Accuracy, F1-score for classification) to rank models.
- **Prediction Service**: A high-performance service for serving real-time or batch predictions using the best-selected model.

4. Data Storage Components

- **Raw Data Store**: Object storage (safe & scalable) like **AWS S3** or **MinIO** for storing large dataset files.
- **Metadata Database**: A relational database (e.g., **PostgreSQL**) to store user info, project metadata, model configurations, and training logs.
- **Model Registry**: A dedicated storage for serialized model artifacts (e.g., `.pkl`, `.h5` files), often versioned (e.g., **MLflow**).
- **Feature Store**: Optional high-speed storage (e.g., **Redis**) to serve precomputed features for low-latency inference.

5. Message Queue / Event Bus

- **Description**: An asynchronous communication backbone (e.g., **Kafka**, **RabbitMQ**).
- **Responsibility**:
  - Decouples services. for example, the *Ingestion Service* publishes a "DataUploaded" event, which triggers the *Preprocessing Service*.
  - Ensures reliability by buffering tasks if the training workers are busy.

Component Interaction Diagram