

# Logistic Regression Model for Breast Cancer Prediction

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## 1. Introduction

This project implements a logistic regression model to predict the likelihood of breast cancer based on the mean radius of a tumor. The model is built using Python and the scikit-learn library, with a custom logistic regression class. The application provides an API using FastAPI and a front-end interface for user interaction.

## 2. Files in the Submission

- i. LogisticRegression3400.ipynb: Implements a logistic regression model using gradient descent in Jupyter Notebook and also contains the model training process.
- ii. LogisticRegression3400.py: Contains the implementation of a custom logistic regression model using Python, including options for L1, L2, and L1+L2 regularization. Generated in VsCode terminal using command-

```
PS C:\Users\KIIT\Desktop\22053400\2) Logistic Regression with L1,L2,L1+L2 regularization> jupyter nbconvert --to script LogisticRegression3400.ipynb
```

- iii. main.py: Defines the FastAPI server to handle prediction requests.
- iv. model.pkl: The trained model serialized using pickle.
- v. index.html: Front-end UI for user input and displaying predictions.

## 3. Installation and Setup

- i. Prerequisites :- Required Python packages: Numpy, scikit-learn, fastapi, pickle, uvicorn.
  - NumPy (*numpy*) is used for numerical computations and matrix operations in model training.
  - Scikit-learn (*sklearn*) is used for loading the dataset and provides ML utilities.
  - FastAPI (*fastapi*) is used to create a web API for serving predictions.
  - Pickle (*pickle*) is used to save and load the trained model for reuse.
  - Uvicorn (*uvicorn*) is used to run the FastAPI server asynchronously.
- ii. Installing Dependencies:- The following command is used in vscode terminal to install dependencies

```
PS C:\Users\KIIT\Desktop\22053400\2) Logistic Regression with L1,L2,L1+L2 regularization> pip install fastapi uvicorn numpy pandas scikit-learn
```

## 4. Model Implementation

The LogisticRegressionCustom class in LogisticRegression3400.py implements a logistic regression model with gradient descent optimization and optional regularization (L1, L2, or L1+L2). The model predicts the probability of breast cancer based on tumor features.

```
class LogisticRegressionCustom:
    def __init__(self, learning_rate=0.01, epochs=1000, reg_type=None, lambda_=0.01):
        self.learning_rate = learning_rate
        self.epochs = epochs
        self.reg_type = reg_type
        self.lambda_ = lambda_
        self.weights = None
        self.bias = None

    def sigmoid(self, z):
        return 1 / (1 + np.exp(-z))

    def fit(self, X, y):
        n_samples, n_features = X.shape
        self.weights = np.zeros(n_features)
        self.bias = 0

        for _ in range(self.epochs):
            model = np.dot(X, self.weights) + self.bias
            y_predicted = self.sigmoid(model)
            error = y_predicted - y
            dw = (1/n_samples) * np.dot(X.T, error)
            db = (1/n_samples) * np.sum(error)
            if self.reg_type == "L1":
                dw += self.lambda_ * np.sign(self.weights)
            elif self.reg_type == "L2":
                dw += self.lambda_ * self.weights
            elif self.reg_type == "L1+L2":
                dw += self.lambda_ * (np.sign(self.weights) + self.weights)
            self.weights -= self.learning_rate * dw
            self.bias -= self.learning_rate * db

    def predict_proba(self, X):
        """ Returns the probability of the sample being in class 1 """
        model = np.dot(X, self.weights) + self.bias
        return self.sigmoid(model)

    def predict(self, X, threshold=0.6):
        """ Returns class labels based on a probability threshold """
        probabilities = self.predict_proba(X)
        return (probabilities >= threshold).astype(int)
```

## 5. Training the Model

- The dataset used is the Breast Cancer Dataset from sklearn.datasets.
- The model is trained on the Mean Radius feature ( $X = \text{data.data[:, 0]}$ ) to predict the target ( $y = \text{data.target}$ ).
- The training process uses gradient descent with 1000 epochs and L2 regularization.

- The input feature is normalized using Min-Max scaling.
- After training, the model is saved using pickle.

## 6. API Implementation

The FastAPI-based backend (main.py) loads the trained model and provides an endpoint to make predictions:

### i. API Setup

```
8 app = FastAPI()
```

### ii. CORS Configuration- To allow front-end requests:

```
10 app.add_middleware(
11     CORSMiddleware,
12     allow_origins=["*"],
13     allow_methods=["*"],
14     allow_headers=["*"],
15 )
```

### iii. Loading the Trained Model

```
with open("model.pkl", "wb") as file:
    pickle.dump(model, file)
```

### iv. Defining the API Endpoint

```
23 @app.post("/predict")
24 def predict(data: CancerInput):
25     input_value = np.array([[data.mean_radius]])
26     min_value, max_value = 6.981, 28.11
27     input_value = (input_value - min_value) / (max_value - min_value)
28     probability = float(model.predict_proba(input_value)[0])
29     prediction = int(probability < 0.6)
30     return {"probability": round(probability, 2), "prediction": prediction}
31
```

## 7. Running the Application (FastAPI Server)

The following command is used in vscode to start the API server:

```
PS C:\Users\KIIT\Desktop\22053400\2) Logistic Regression with L1,L2,L1+L2 regularization> uvicorn main:app --reload
INFO: Will watch for changes in these directories: ['C:\Users\KIIT\Desktop\22053400\2) Logistic Regression with L1,L2,L1+L2 regularization']
INFO: Uvicorn running on http://127.0.0.1:8000 (Press CTRL+C to quit)
INFO: Started reloader process [8496] using WatchFiles
INFO: Started server process [8784]
INFO: Waiting for application startup.
INFO: Application startup complete.
```

## 8. Front-End Implementation

The index.html file provides a simple UI for users to input mean radius values and get predictions using the API. It has inline CSS and JavaScript. The JavaScript function sends a request to the FastAPI backend:

```

114     function predict() {
115         let meanRadiusValue = document.getElementById("mean_radius").value;
116
117         fetch("http://127.0.0.1:8000/predict", {
118             method: "POST",
119             headers: {
120                 "Content-Type": "application/json"
121             },
122             body: JSON.stringify({ mean_radius: parseFloat(meanRadiusValue) })
123         })
124         .then(response => response.json())
125         .then(data => {
126             let resultText = data.prediction === 1 ? "Malignant (Cancerous)" : "Benign (Non-Cancerous)";
127             document.getElementById("result").innerHTML =
128                 "Prediction: " + resultText + " (Probability: " + data.probability + ")";
129         })
130         .catch(error => console.error("Error:", error));
131     }

```

## 9. Conclusion

This project successfully implements a logistic regression model to predict breast cancer based on the mean radius of a tumor. The model is integrated with a FastAPI backend, using NumPy for numerical computations and Scikit-learn for dataset handling. The trained model is saved using Pickle and deployed via Uvicorn for real-time predictions. The frontend layout features a centered card with a dark-themed background, rounded corners, and a shadow effect. At the top, a bold gold header displays the title "Breast Cancer Prediction," followed by a welcoming message and a brief description of the tool. Below, a user input field for Mean Radius is provided, along with a "Predict" button, which displays the predicted cancer likelihood underneath upon submission.

## BREAST CANCER PREDICTION

### Welcome to Breast Cancer Prediction

This tool helps predict breast cancer likelihood based on the mean radius of the tumor. Enter the value below to receive a prediction.

**Enter Mean Radius:**

1.75

Predict

Prediction: Benign (Non-Cancerous)

(Probability: 0.65)

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