import numpy as np

import matplotlib.pyplot as plt

from scipy.stats import norm, uniform, beta

# Observed data

observed\_height = 1.7

# Define the range for the mean height (μ)

mu\_values = np.linspace(1.65, 1.8, 50)

# Define the Prior

# Uniform prior: All values between 1.65 and 1.8 are equally likely

prior\_uniform = uniform.pdf(mu\_values, 1.65, 1.8 - 1.65)

# Beta prior: More weight towards shorter heights

alpha, beta\_param = 2, 5

prior\_beta = beta.pdf((mu\_values - 1.65) / (1.8 - 1.65), alpha, beta\_param)

# Define the Likelihood

# Assuming a standard deviation (σ) of 0.1m for the normal distribution

sigma = 0.1

likelihood = norm.pdf(observed\_height, mu\_values, sigma)

# Calculate the Posterior (unnormalized)

unnormalized\_posterior\_uniform = prior\_uniform \* likelihood

unnormalized\_posterior\_beta = prior\_beta \* likelihood

# Normalize the posterior

posterior\_uniform = unnormalized\_posterior\_uniform / np.sum(unnormalized\_posterior\_uniform)

posterior\_beta = unnormalized\_posterior\_beta / np.sum(unnormalized\_posterior\_beta)

# Visualization

plt.figure(figsize=(10, 6))

plt.plot(mu\_values, prior\_uniform, label='Uniform Prior', linestyle='--')

plt.plot(mu\_values, prior\_beta, label='Beta Prior', linestyle='--')

plt.plot(mu\_values, likelihood, label='Likelihood', linestyle='-.')

plt.plot(mu\_values, posterior\_uniform, label='Posterior (Uniform Prior)', linewidth=2)

plt.plot(mu\_values, posterior\_beta, label='Posterior (Beta Prior)', linewidth=2)

plt.xlabel('Mean Height (μ)')

plt.ylabel('Probability Density')

plt.title('Bayesian Analysis: Prior, Likelihood, and Posterior')

plt.legend()

plt.grid(True)

plt.show()