Evaluation - 02

HPC

FACE RECOGNITION

Using PCA, LDA, Fisherfaces

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PROJECT OVERVIEW

PROBLEM STATEMENT

- Facial recognition systems require significant computational resources due to high-dimensional data processing
- Traditional sequential implementations of PCA and LDA algorithms are computationally intensive
- Need for faster processing for real-time facial recognition applications
- Challenge of optimizing performance while maintaining accuracy

OBJECTIVES

1. Implement and optimize PCA and LDA algorithms for facial recognition
2. Develop parallel implementations using:
   - OpenMP (CPU parallel processing)
   - CUDA (GPU acceleration)
3. Compare performance metrics between:
   - Sequential implementation
   - OpenMP parallel implementation
   - CUDA parallel implementation
4. Achieve significant speedup while maintaining recognition accuracy

DATASET AND TOOLS

- Dataset: AT&T Face Dataset on Kaggle
- 40 subjects, 10 grayscale images each (size: 112x92).

Tools :

- C++ for algorithm logic
- openCV
- CUDA/OpenMP (planned)

Environment :

- Multi-core CPU (for OpenMP)
- CUDA-compatible GPU (for parallel acceleration)

PRINCIPAL COMPONENT ANALYSIS (PCA)

- - Dimensionality reduction technique
- - Transforms high-dimensional data into lower-dimensional space
- - Preserves maximum variance in the data

Eigenfaces Approach

- Represents faces as linear combinations of base faces

- Reduces facial images to principal components

- Maintains essential features while reducing data size

Working Process

- Compute mean face from training images

- Calculate covariance matrix

- Extract eigenvectors (eigenfaces)

- Project faces onto eigenface space

LINEAR DISCRIMINANT ANALYSIS (LDA)

- Supervised learning algorithm ,Focus on maximizing class separability ,Finds optimal projection for classification

Fisherfaces Approach

- Maximizes between-class scatter
- Minimizes within-class scatter
- Better handling of lighting and expression variations

Working Process

- Calculate within-class and between-class scatter matrices
- Compute eigenvectors of scatter matrices
- Project data onto discriminant space
- Optimize class separation

APPLICATION IN FACIAL RECOGNITION – PCA – 1

- Converts high-dimensional data into a lower-dimensional space while retaining maximum variance.

1. **Data Preprocessing**
   - Load PGM images and normalize pixel values.
   - Compute the mean face vector.
   - Center the data by subtracting the mean face vector.

2. **Covariance Matrix Computation:**
   - Calculate the covariance matrix using the centered data.

3. **Eigenvector and Eigenvalue Computation**
   - Use power iteration to compute eigenvalues and eigenvectors.
   - Select top 'k' eigenvectors as eigenfaces.

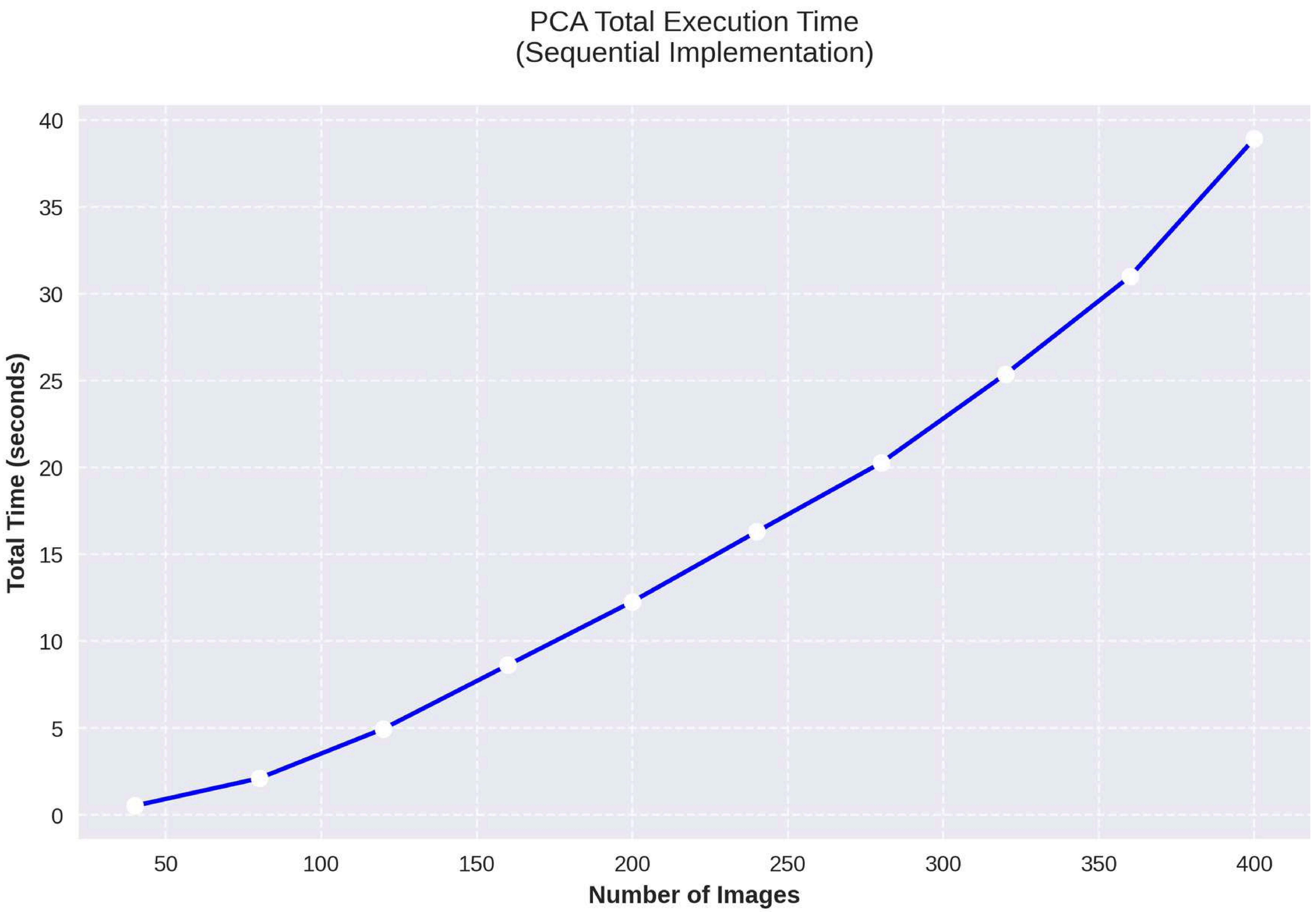
APPLICATION IN FACIAL RECOGNITION – PCA – 2

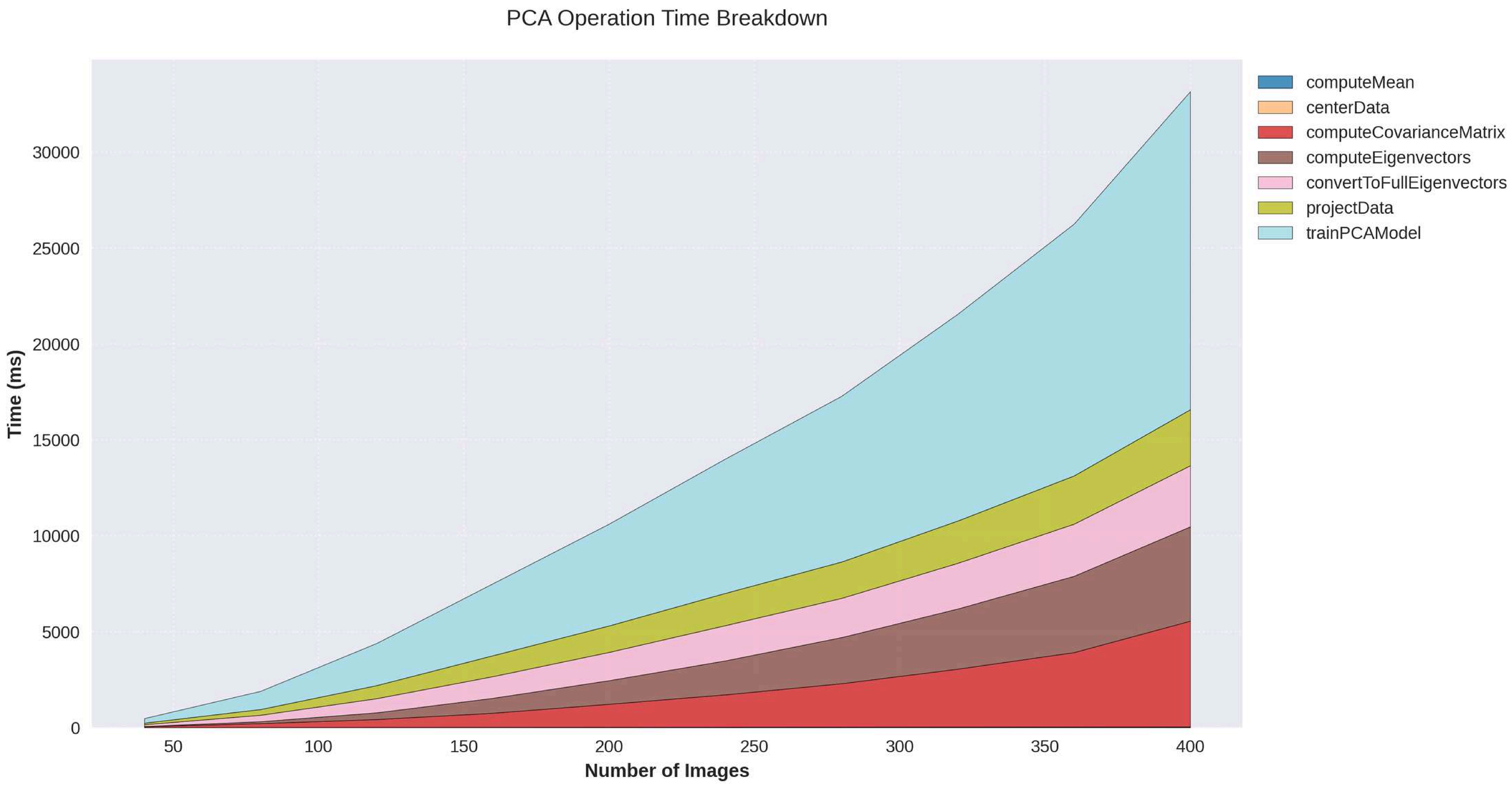
4. Projection and Recognition

- Project training and test data onto the eigenfaces.
- Use Euclidean distance to find the nearest match in the feature space.

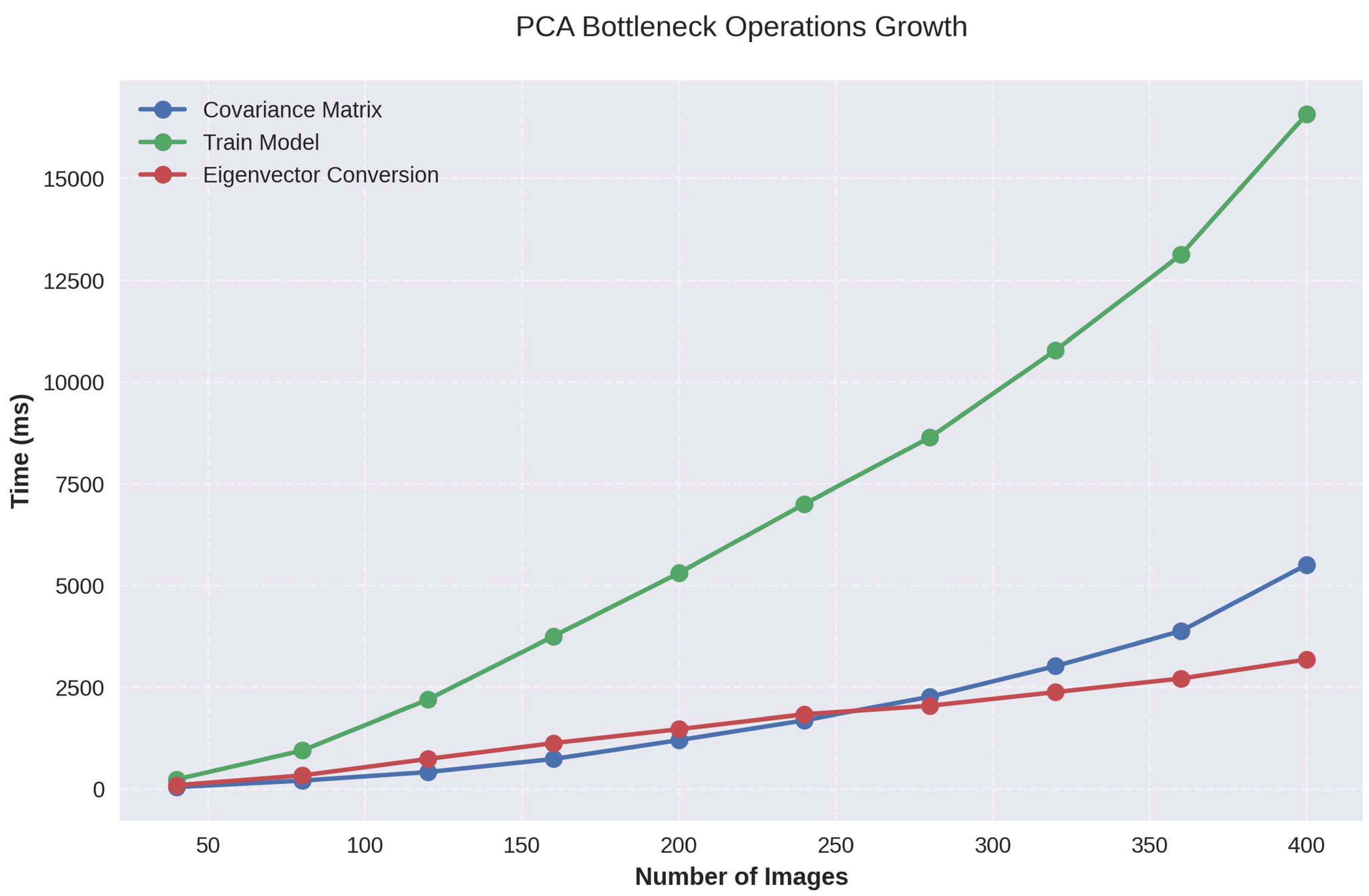
5. Output

- Save the mean face and eigenfaces as PGM files.
- Display recognition accuracy.


PCA Total Execution Time
(Sequential Implementation)
Total Time (seconds)
Number of Images
0
5
10
15
20
25
30
35
40
50
100
150
200
250
300
350
400



PCA Operation Time Breakdown
computeMean
centerData
computeCovarianceMatrix
computeEigenvectors
convertToFullEigenvectors
projectData
trainPCAModel
Time (ms)
0
5000
10000
15000
20000
25000
30000
50
100
150
200
250
300
350
400
Number of Images


PCA Bottleneck Operations Growth
Covariance Matrix
Train Model
Eigenvector Conversion
Time (ms)
0
2500
5000
7500
10000
12500
15000
50
100
150
200
250
300
350
400
Number of Images

AREAS FOR PARALLELIZATION – PCA 1

1. Normalization of Pixel Values

- Normalize images by dividing each pixel by the maximum value.
- Parallelization: Distribute the computation of pixel normalization across threads (OpenMP) or CUDA blocks.

2. Mean Vector Computation

- Compute the mean of all training images pixel-wise.
- Parallelization: Sum the pixel values across images in parallel.

3. Centering the Data

- Subtract the mean vector from each image.
- Parallelization: Process each image independently.

AREAS FOR PARALLELIZATION – PCA 2

4. Covariance Matrix Computation

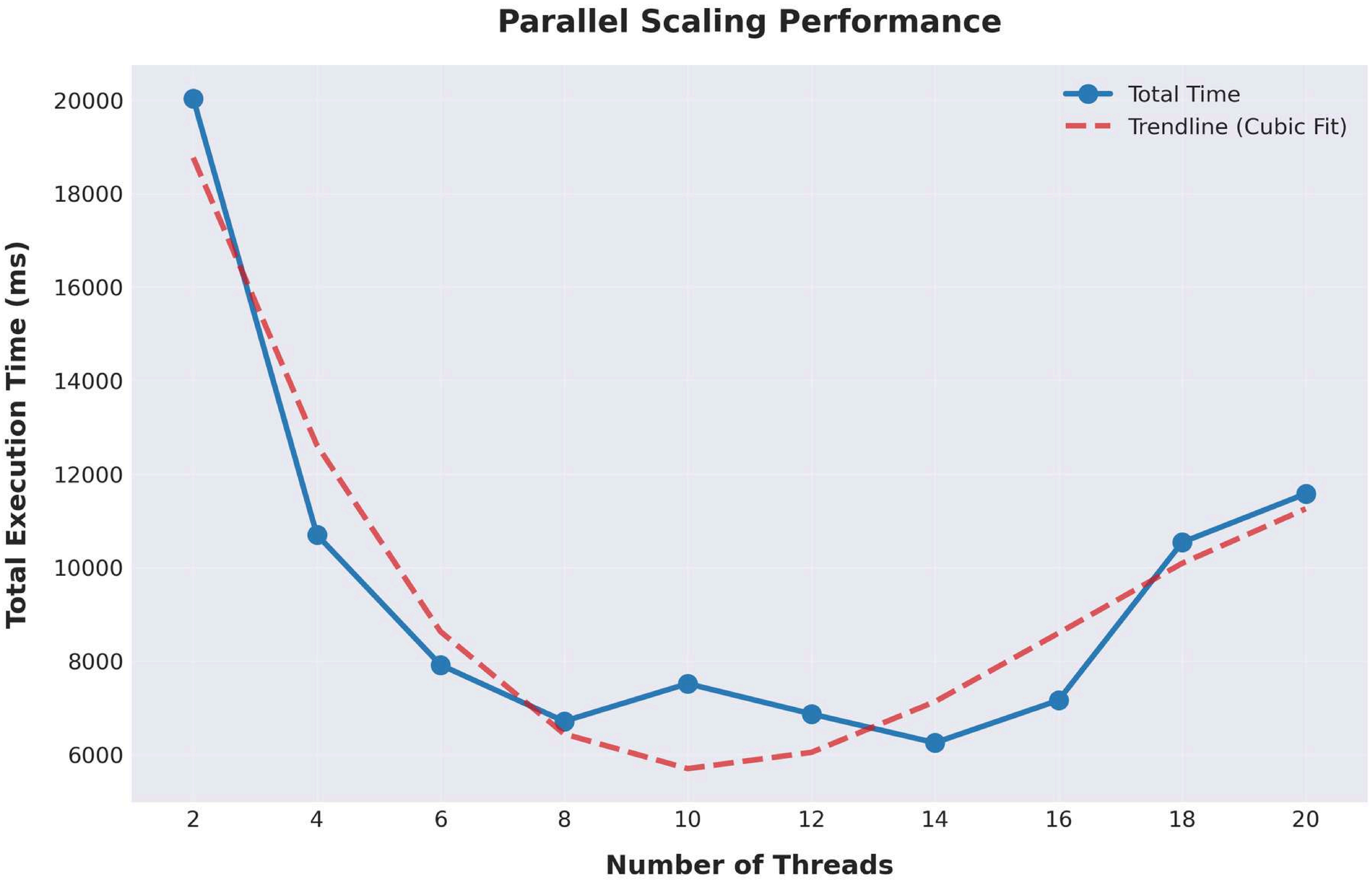
- Calculate the covariance matrix using matrix multiplication.
- Parallelization: Perform matrix multiplications in parallel using OpenMP or CUDA.

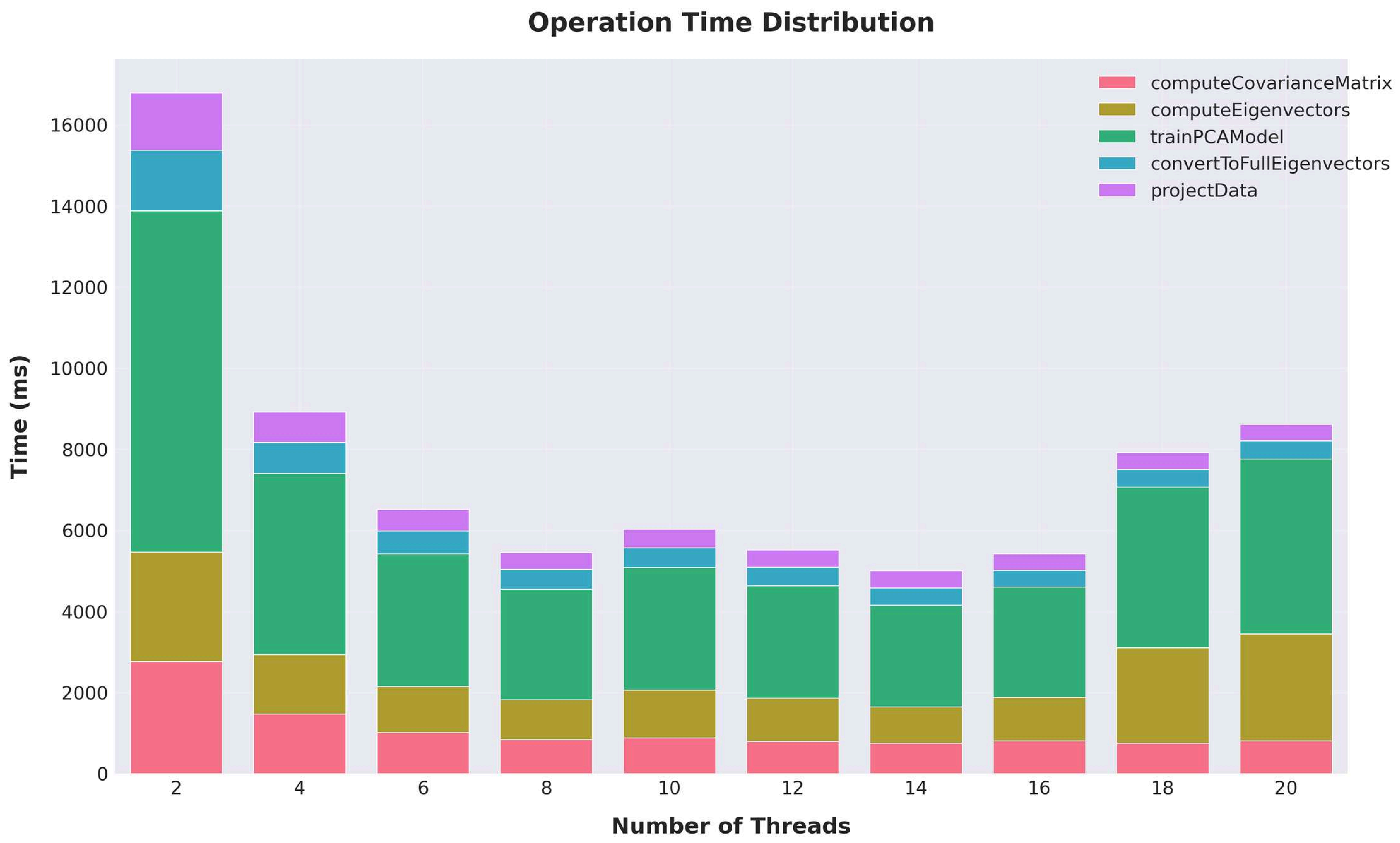
5. Eigenvalue and Eigenvector Computation

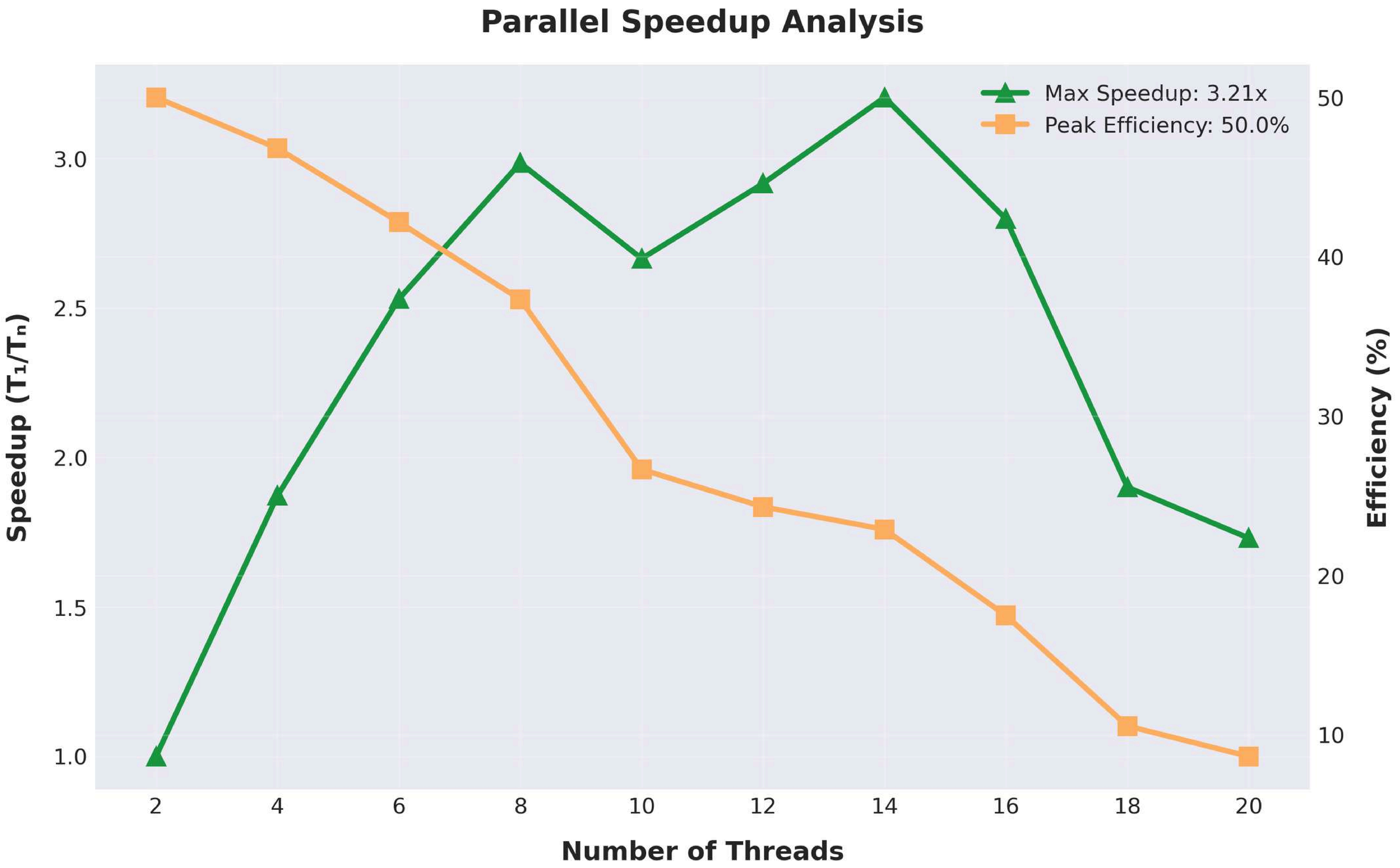
- Use power iteration to compute eigenvalues and eigenvectors.
- Parallelization: Parallelize the matrix-vector multiplications within each iteration.

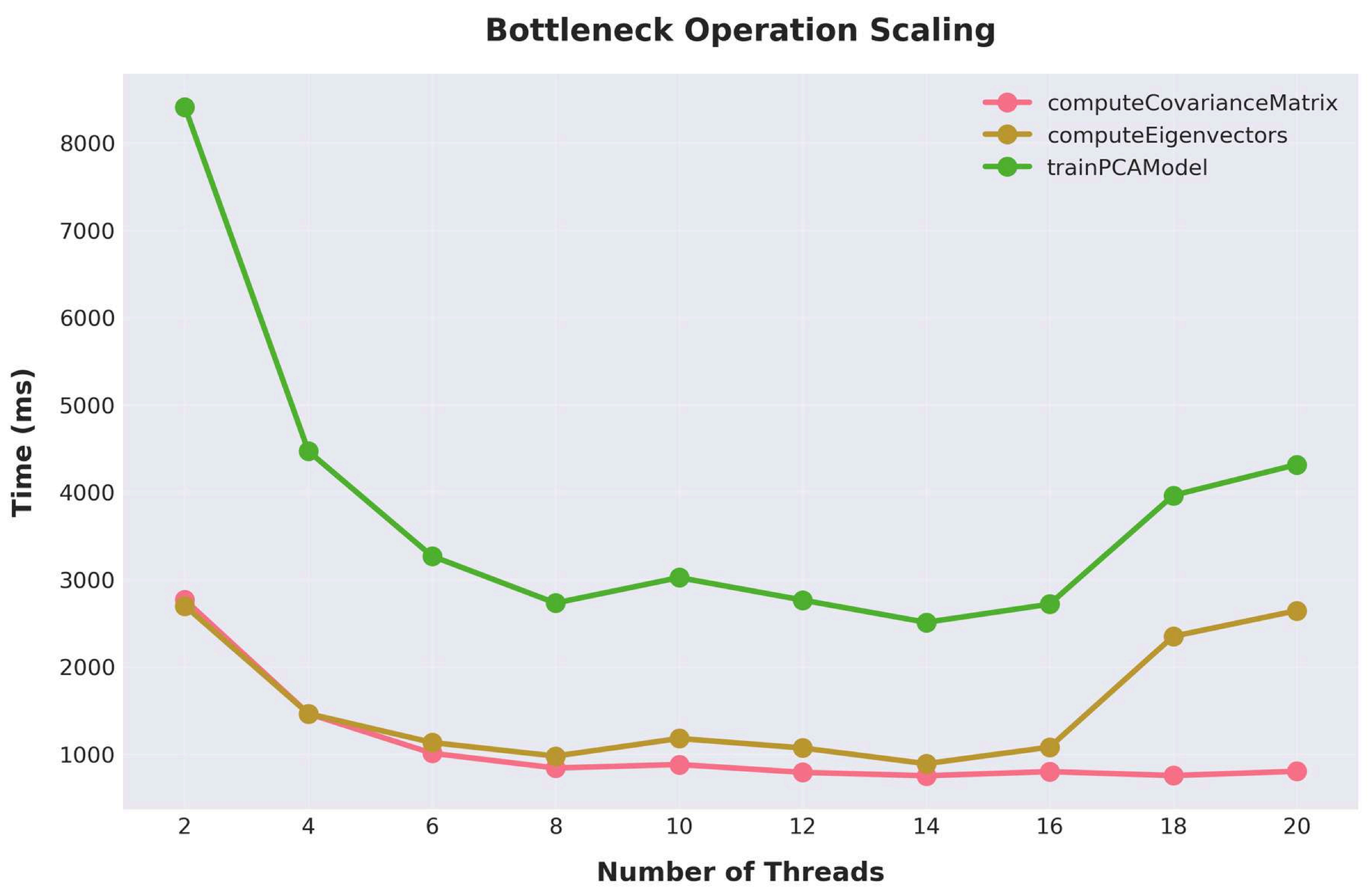
6. Projection onto Eigenfaces

- Project the training and test data onto the top 'k' eigenvectors.
- Parallelization: Process each image independently during projection.

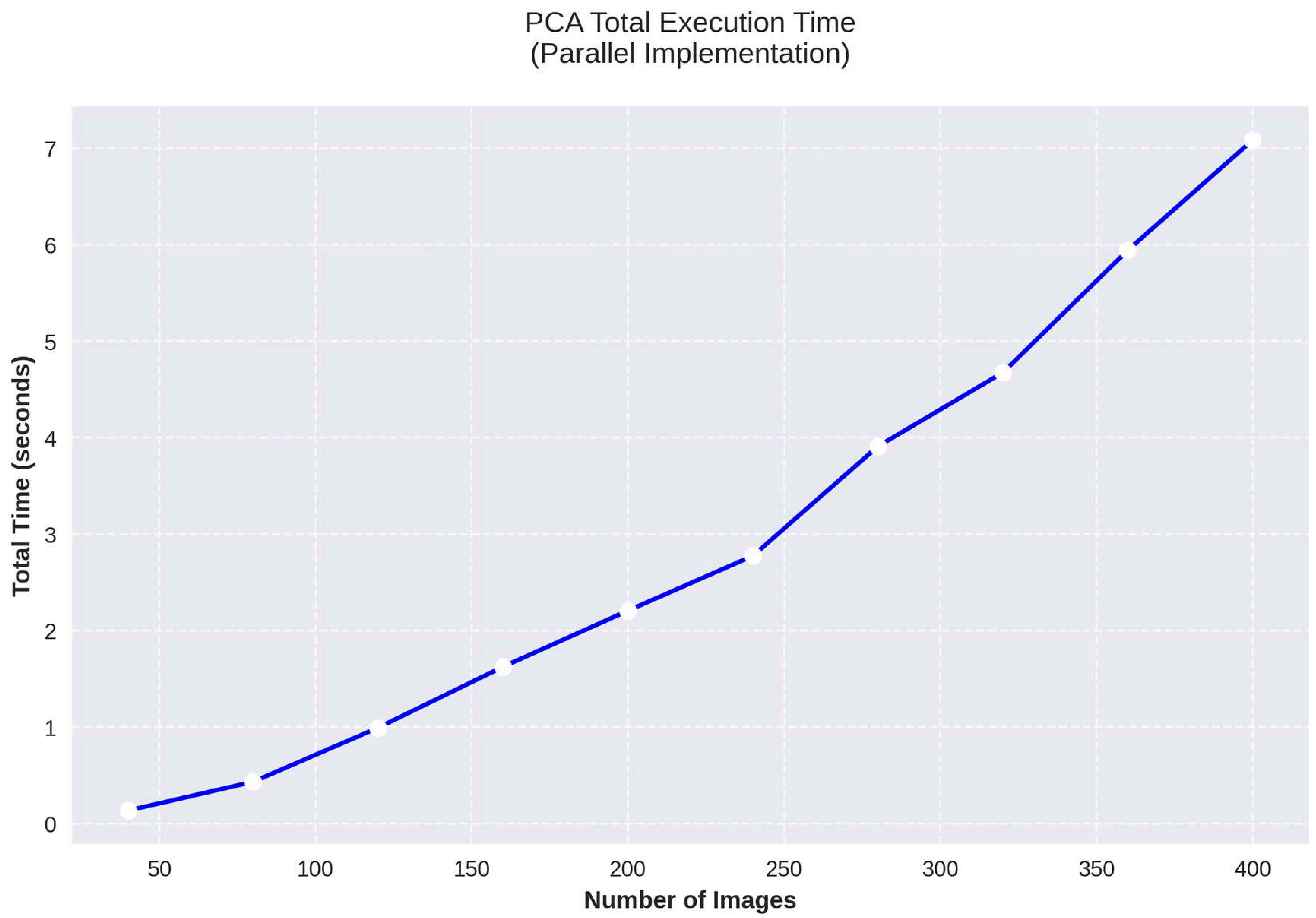

Parallel Scaling Performance
Total Time
Trendline (Cubic Fit)
Total Execution Time (ms)
20000
18000
16000
14000
12000
10000
8000
6000
2
4
6
8
10
12
14
16
18
20
Number of Threads

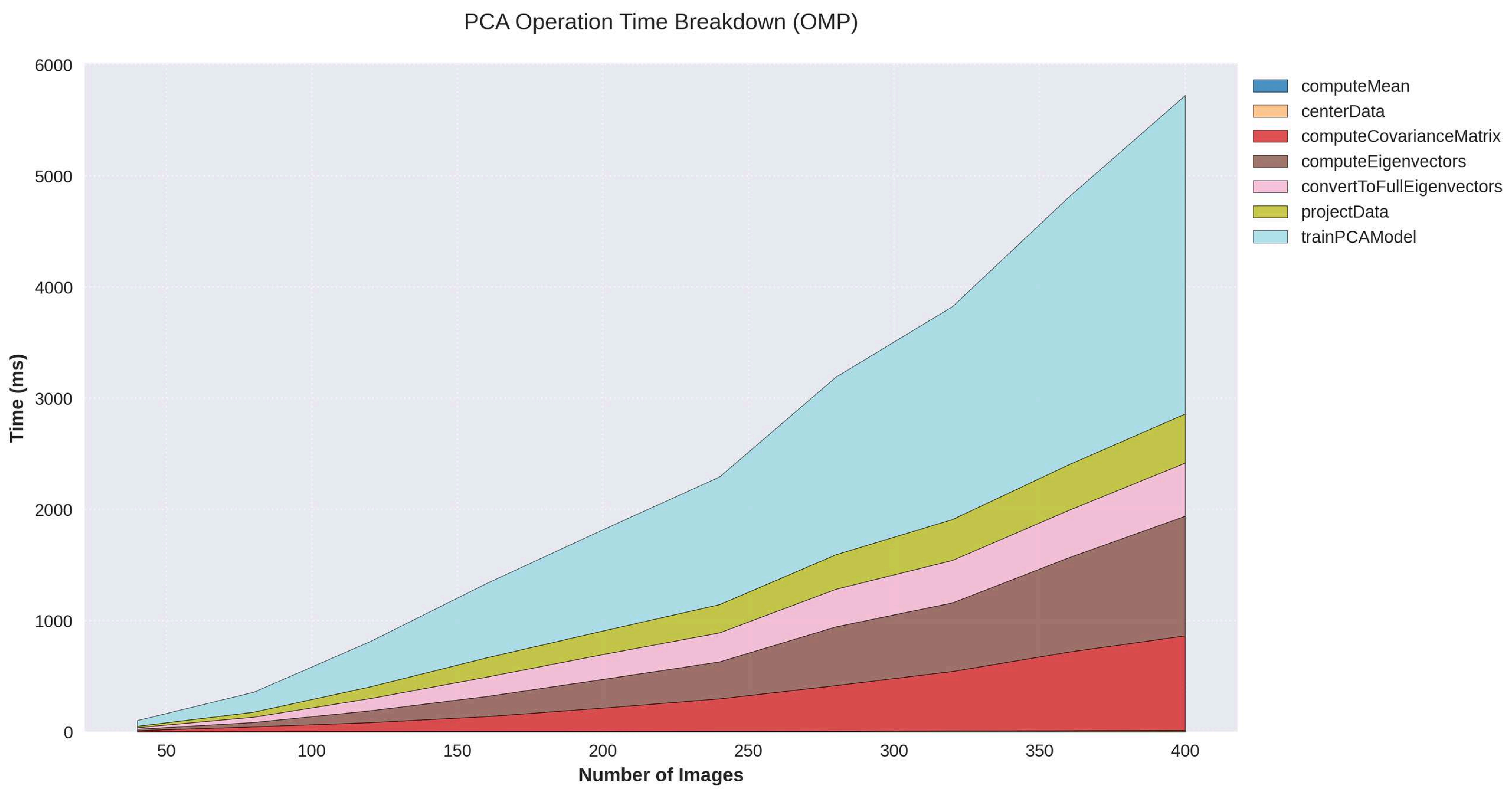

Operation Time Distribution
computeCovarianceMatrix
computeEigenvectors
trainPCAModel
convertToFullEigenvectors
projectData
Time (ms)
0
2000
4000
6000
8000
10000
12000
14000
16000
2
4
6
8
10
12
14
16
18
20
Number of Threads


Parallel Speedup Analysis
Max Speedup: 3.21x
Peak Efficiency: 50.0%
Speedup (T_1/T_n)
Efficiency (%)
Number of Threads
1.0
1.5
2.0
2.5
3.0
10
20
30
40
50
2
4
6
8
10
12
14
16
18
20

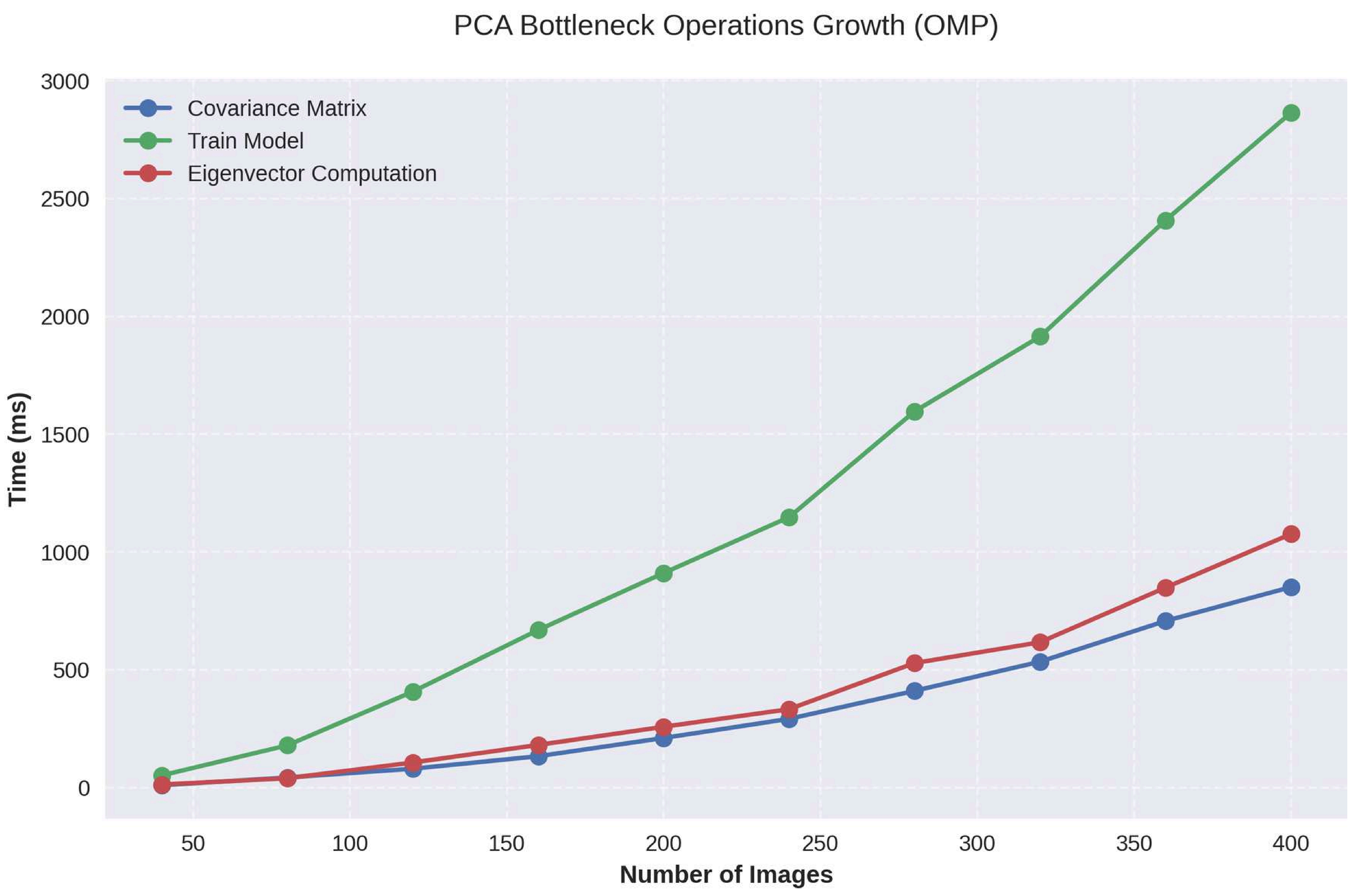


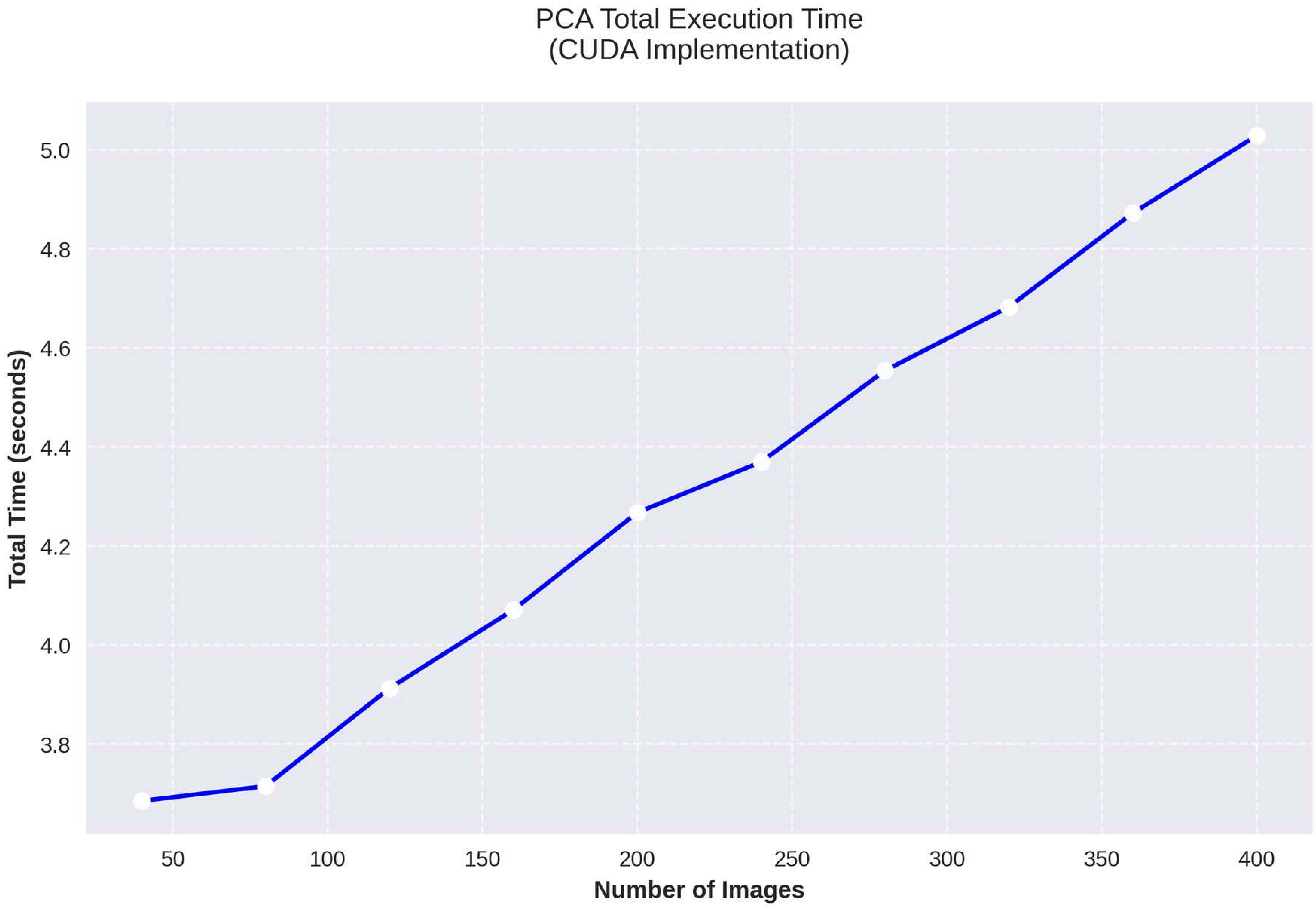
Bottleneck Operation Scaling
computeCovarianceMatrix
computeEigenvectors
trainPCAModel
Time (ms)
8000
7000
6000
5000
4000
3000
2000
1000
2
4
6
8
10
12
14
16
18
20
Number of Threads

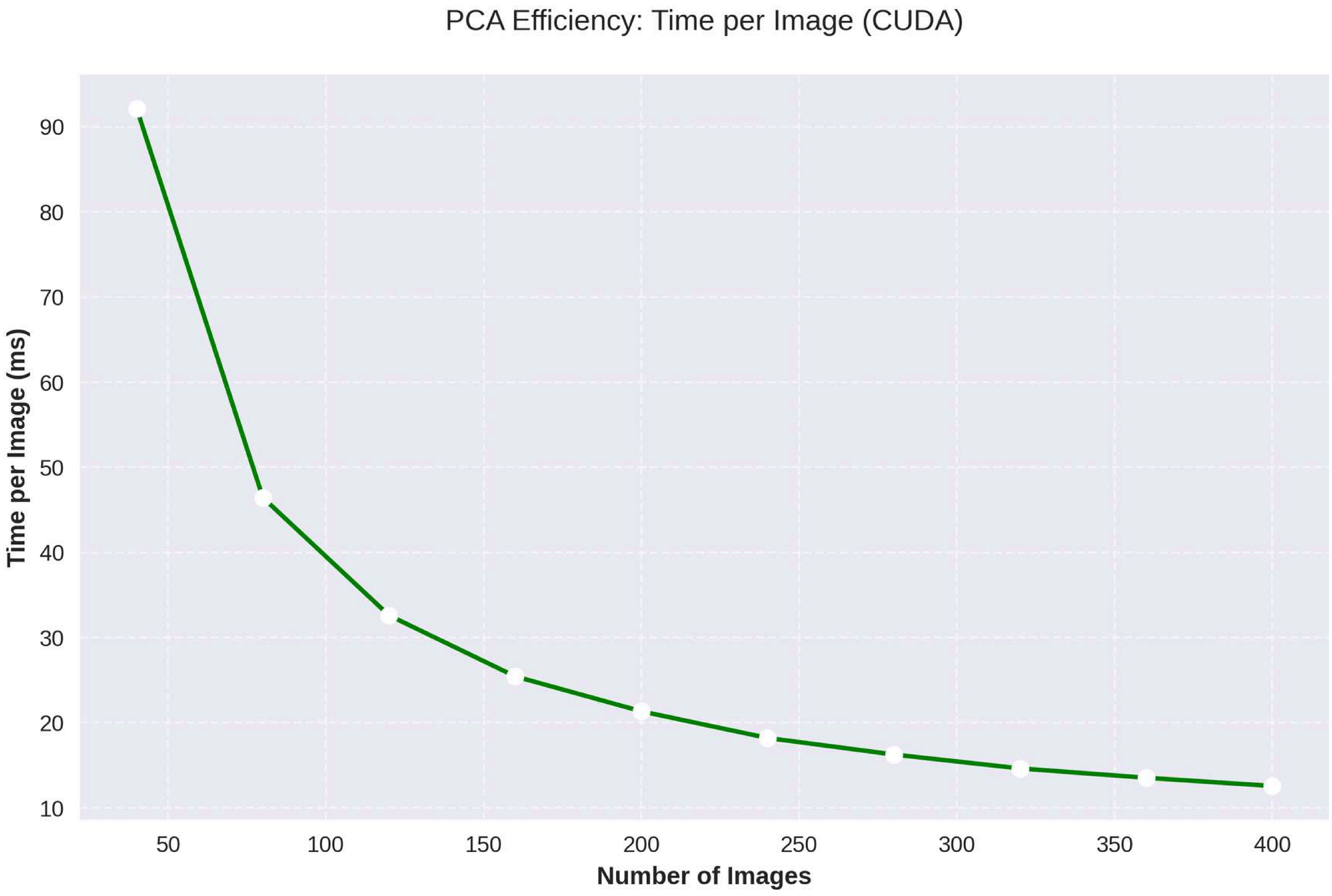

PCA Total Execution Time
(Parallel Implementation)
Total Time (seconds)
0
1
2
3
4
5
6
7
50
100
150
200
250
300
350
400
Number of Images

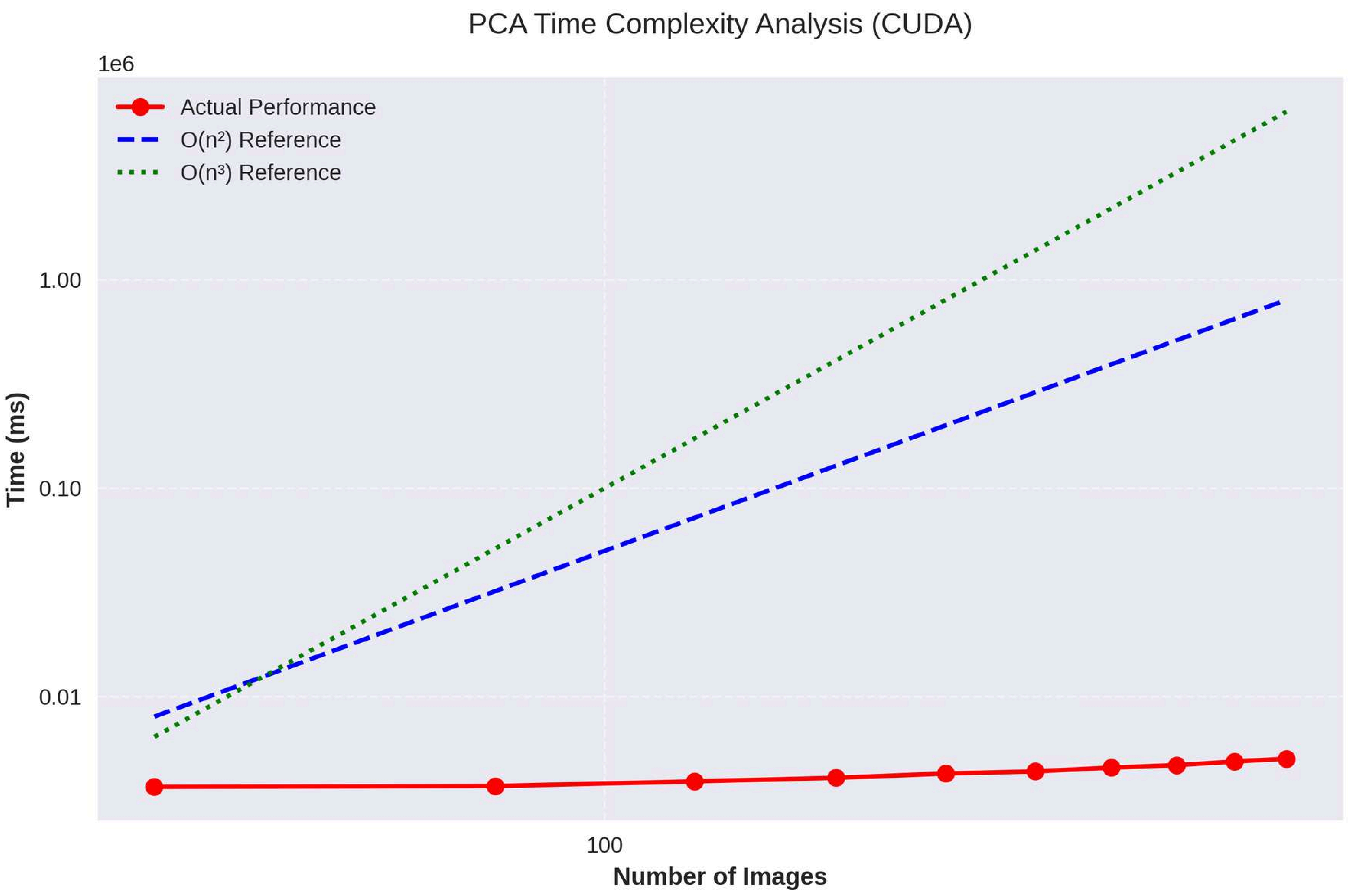

PCA Operation Time Breakdown (OMP)
Time (ms)
0
1000
2000
3000
4000
5000
6000
Number of Images
50
100
150
200
250
300
350
400
computeMean
centerData
computeCovarianceMatrix
computeEigenvectors
convertToFullEigenvectors
projectData
trainPCAModel

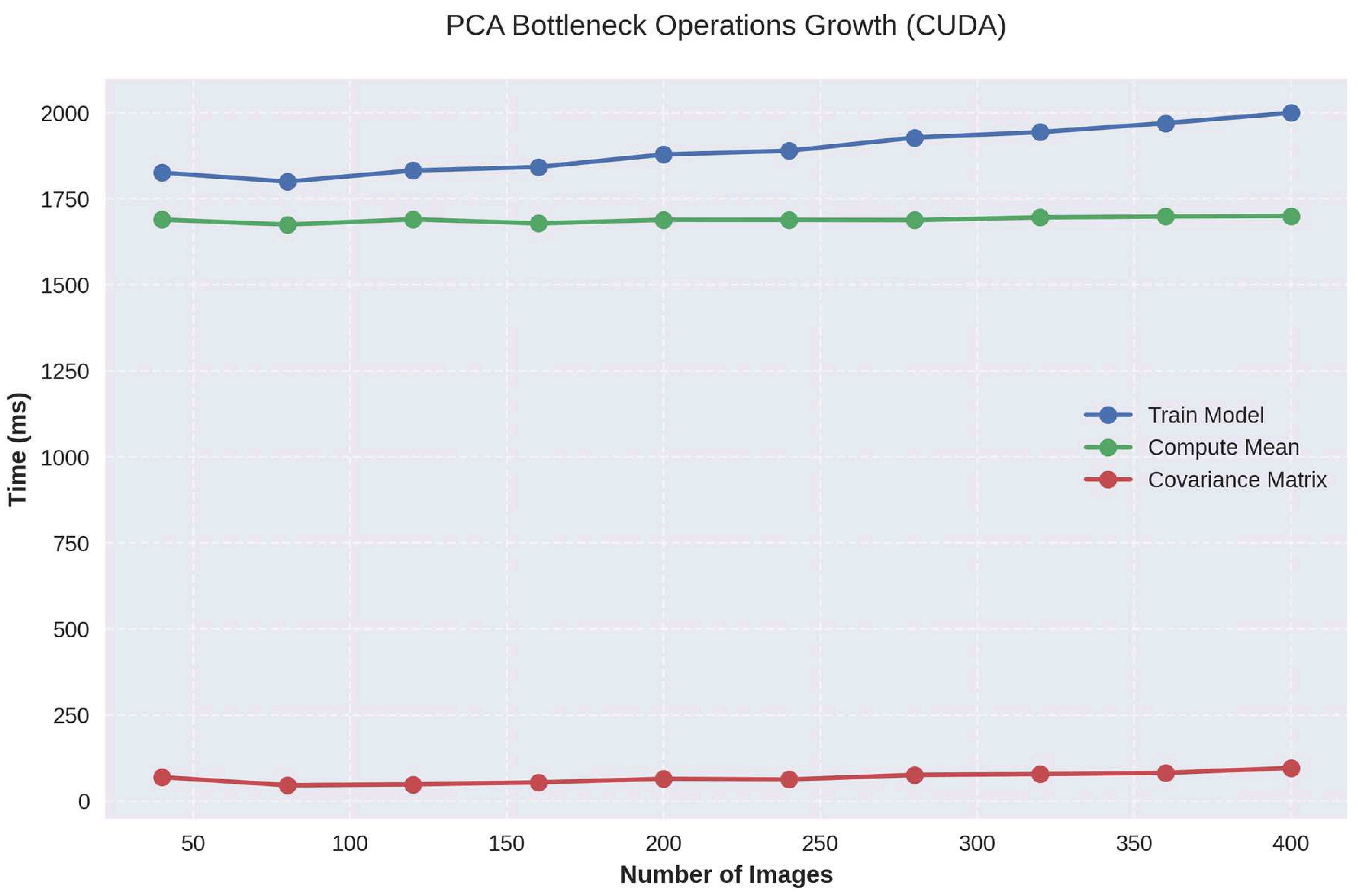

PCA Efficiency: Time per Image (OMP)
Time per Image (ms)
Number of Images
18
16
14
12
10
8
6
4
50
100
150
200
250
300
350
400

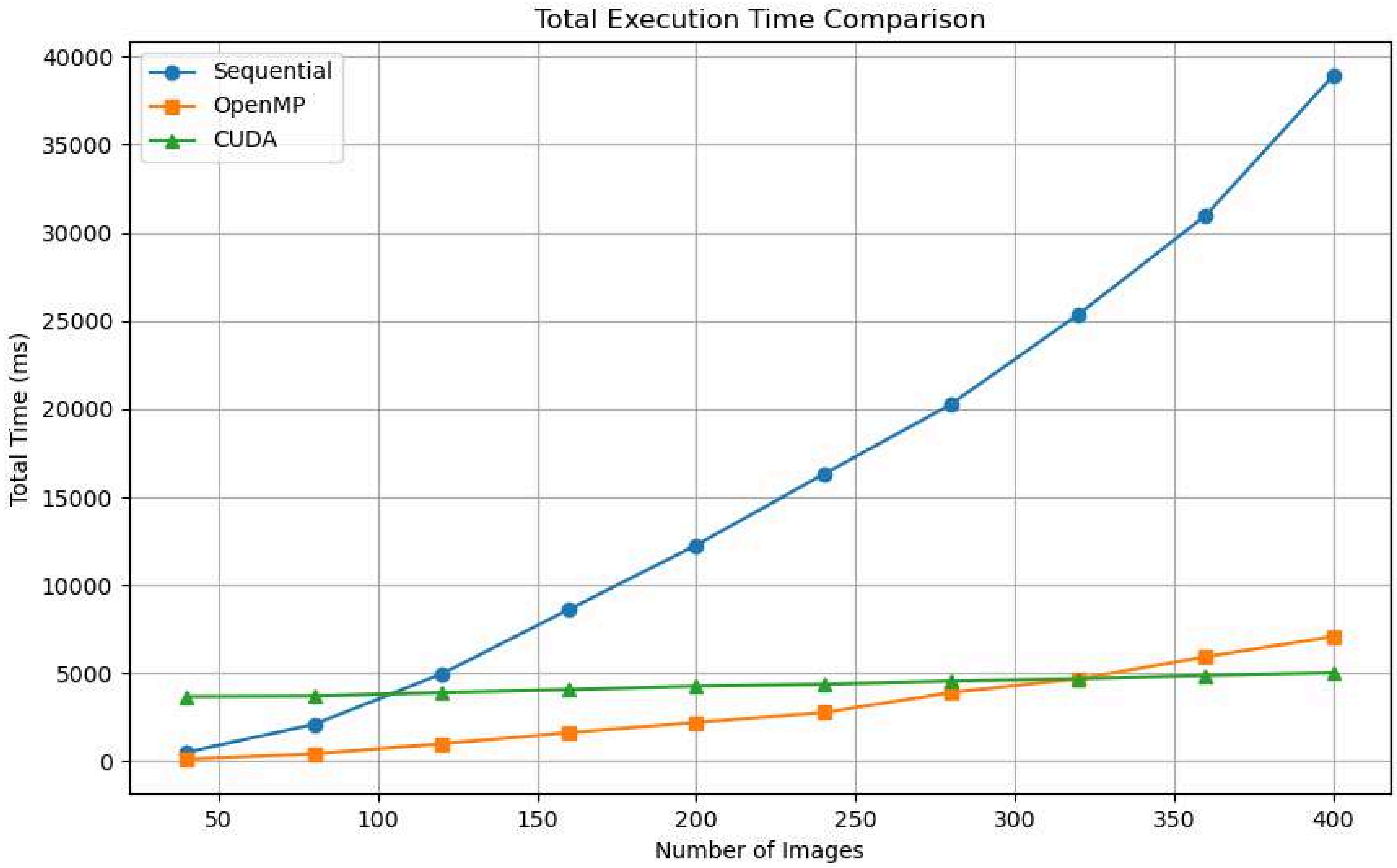

PCA Bottleneck Operations Growth (OMP)
Covariance Matrix
Train Model
Eigenvector Computation
Time (ms)
Number of Images
0
500
1000
1500
2000
2500
3000
50
100
150
200
250
300
350
400


PCA Total Execution Time
(CUDA Implementation)
Total Time (seconds)
5.0
4.8
4.6
4.4
4.2
4.0
3.8
50
100
150
200
250
300
350
400
Number of Images

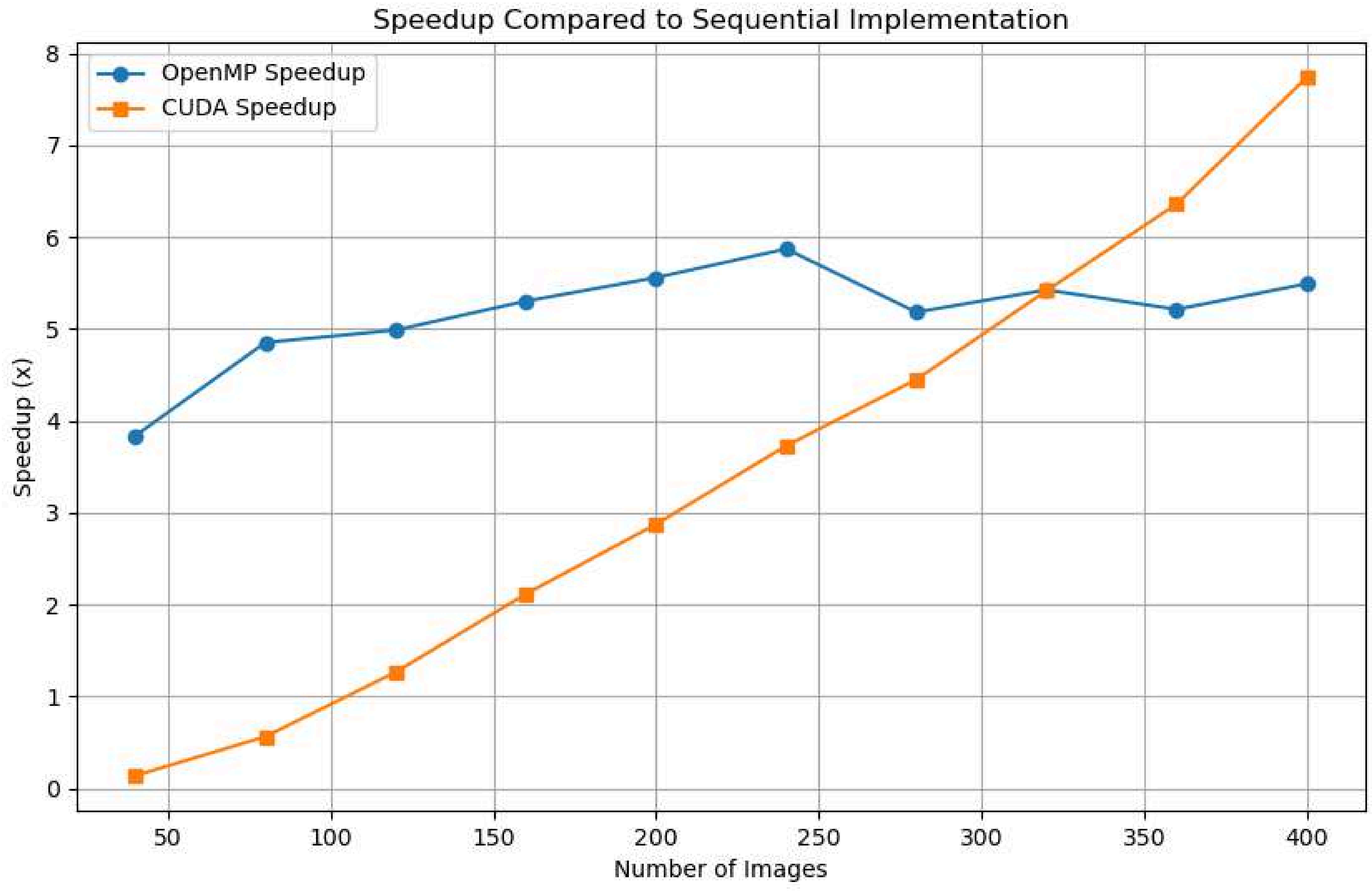

PCA Efficiency: Time per Image (CUDA)
Time per Image (ms)
90
80
70
60
50
40
30
20
10
50
100
150
200
250
300
350
400
Number of Images


PCA Time Complexity Analysis (CUDA)
1e6
Actual Performance
O(n²) Reference
O(n³) Reference
1.00
0.10
0.01
Time (ms)
100
Number of Images

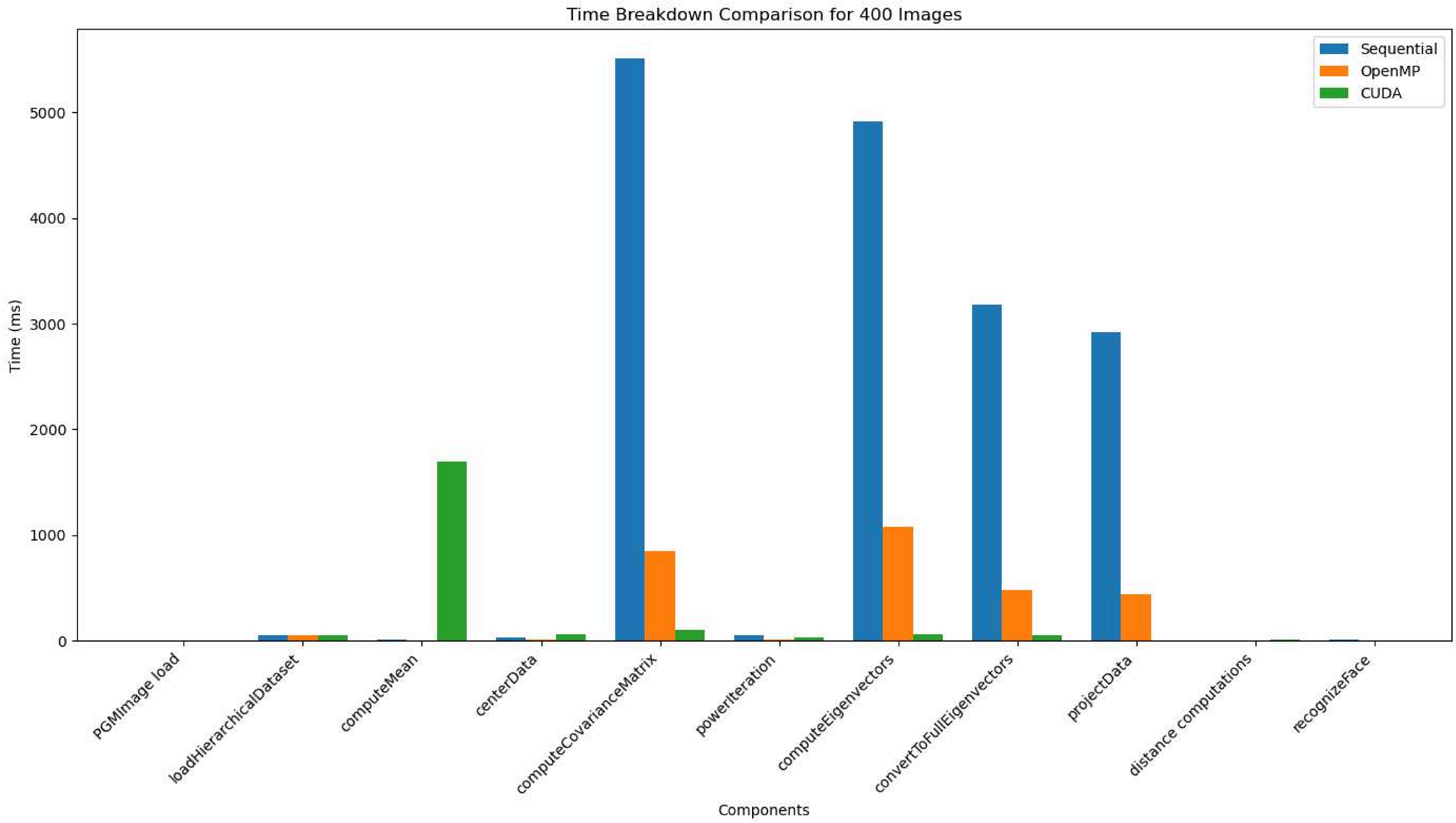

PCA Bottleneck Operations Growth (CUDA)
Time (ms)
0
250
500
750
1000
1250
1500
1750
2000
Number of Images
50
100
150
200
250
300
350
400
Train Model
Compute Mean
Covariance Matrix



Total Execution Time Comparison
Sequential
OpenMP
CUDA
Total Time (ms)
Number of Images
0
5000
10000
15000
20000
25000
30000
35000
40000
50
100
150
200
250
300
350
400



Speedup Compared to Sequential Implementation
OpenMP Speedup
CUDA Speedup
Speedup (x)
Number of Images
0
1
2
3
4
5
6
7
8
50
100
150
200
250
300
350
400


Time Breakdown Comparison for 400 Images
Sequential
OpenMP
CUDA
Time (ms)
0
1000
2000
3000
4000
5000
PGMImage load
loadHierarchicalDataset
computeMean
centerData
computeCovarianceMatrix
powerIteration
computeEigenvectors
convertToFullEigenvectors
projectData
distance computations
recognizeFace
Components

APPLICATION IN FACIAL RECOGNITION – LDA – 1

- Supervised dimensionality reduction technique.
- Maximizes class separability while minimizing within-class variance.

1. **Data Preprocessing**
   - Load PGM images and normalize pixel values.
   - Compute the mean face vector.
   - Center the data by subtracting the mean face vector.

2. **Class-Specific Data Handling**
   - Group samples by class (person ID).
   - Compute within-class and between-class scatter matrices.

3. **PCA as Preprocessing**
   - Apply PCA to reduce dimensionality before applying LDA.

APPLICATION IN FACIAL RECOGNITION – LDA – 2

4. LDA Projection Matrix

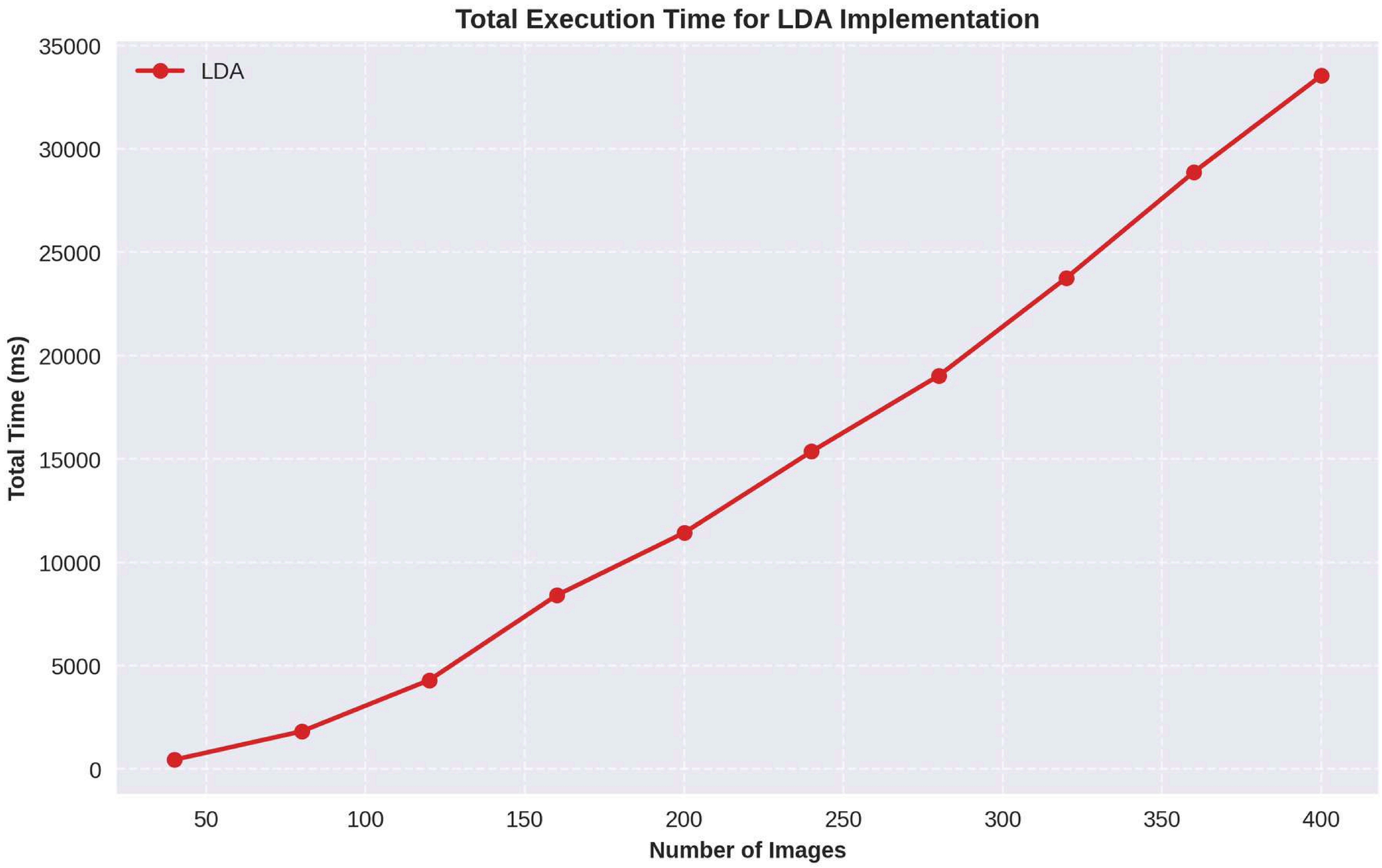
- Solve the generalized eigenvalue problem for SB and SW.
- Compute Fisherfaces in the PCA-reduced space.

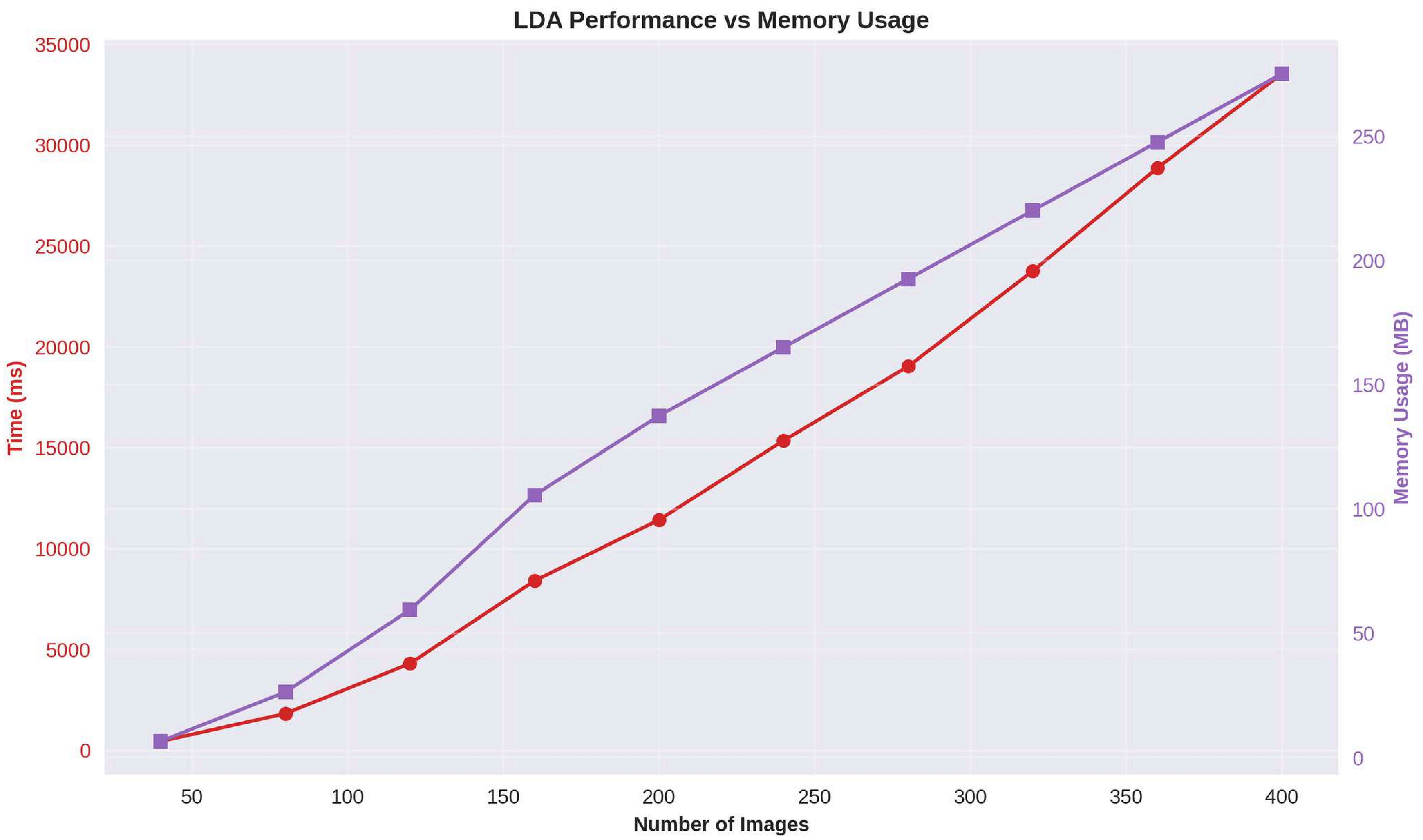
5. Projection and Recognition

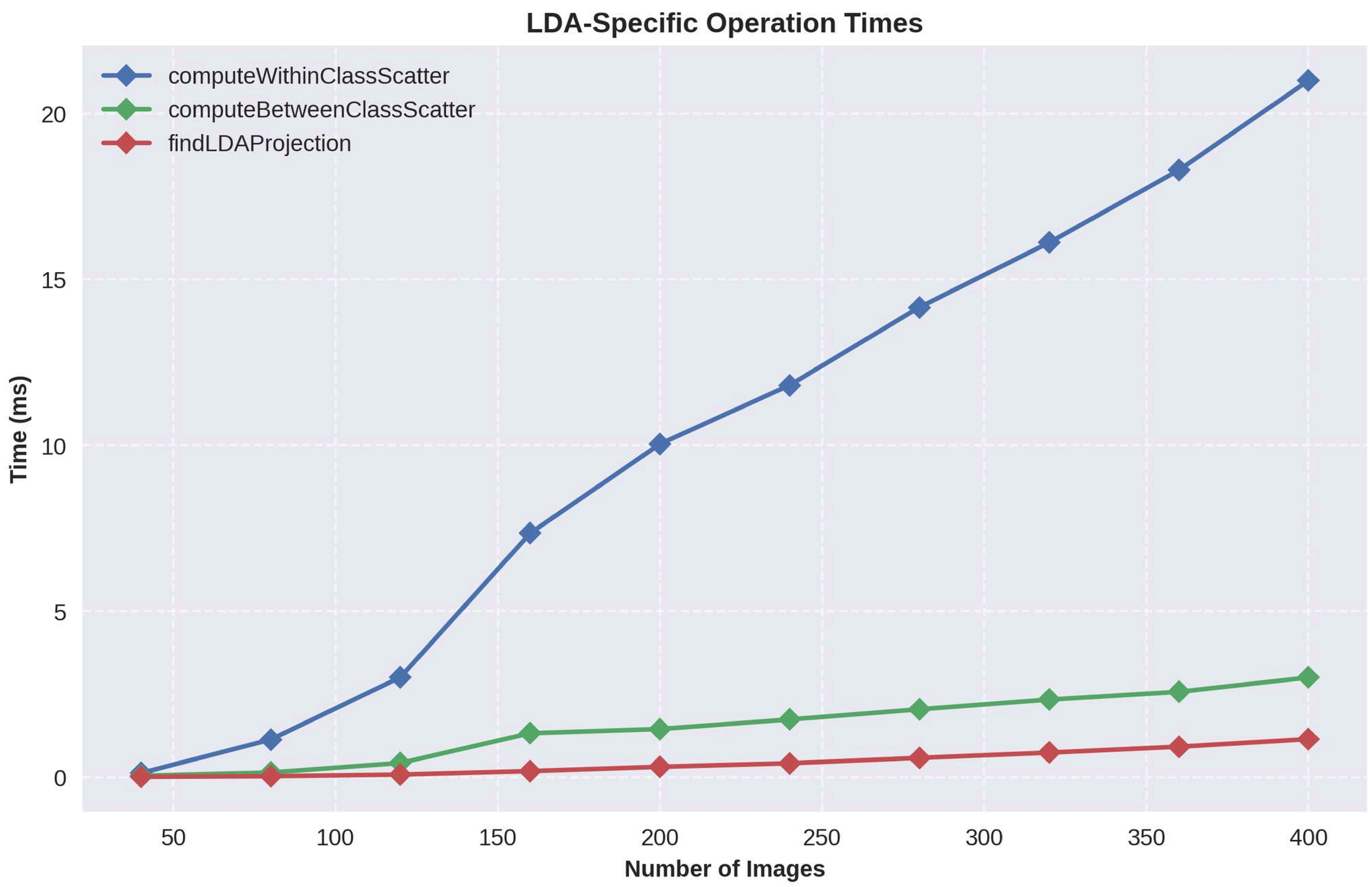
- Project training and test data onto Fisherfaces.
- Use Euclidean distance to find the nearest match.

6. Output

- Save the global mean face and Fisherfaces as PGM files.
- Display recognition accuracy and confusion matrix.


Total Execution Time for LDA Implementation
LDA
Total Time (ms)
35000
30000
25000
20000
15000
10000
5000
0
50
100
150
200
250
300
350
400
Number of Images


LDA Performance vs Memory Usage
Time (ms)
35000
30000
25000
20000
15000
10000
5000
0
Memory Usage (MB)
250
200
150
100
50
0
50
100
150
200
250
300
350
400
Number of Images


LDA-Specific Operation Times
computeWithinClassScatter
computeBetweenClassScatter
findLDAProjection
Time (ms)
0
5
10
15
20
50
100
150
200
250
300
350
400
Number of Images

AREAS FOR PARALLELIZATION – LDA 1

1. **Normalization of Pixel Values**
   - Normalize images by dividing each pixel by the maximum value.
   - Parallelization: Similar to PCA, distribute computation across threads or CUDA blocks.

2. **Global Mean Computation**
   - Compute the global mean vector for all training images.
   - Parallelization: Sum the pixel values across images in parallel.

3. **Within-Class Scatter Matrix (SW) Computation**
   - Compute scatter matrices for each class and sum them.
   - Parallelization: Process each class independently, and parallelize within-class computations.

AREAS FOR PARALLELIZATION – LDA 2

4. Between-Class Scatter Matrix (SB) Computation

- Compute the scatter matrix for the difference between class means and the global mean.
- Parallelization: Each class's computation can run independently.

5. PCA Preprocessing

- Reduce dimensionality using PCA before LDA.
- Parallelization: Apply the same parallelization techniques as in PCA.

6. LDA Projection Matrix Computation

- Solve the generalized eigenvalue problem for SW and SB.
- Parallelization: Parallelize the eigenvalue and eigenvector computation.

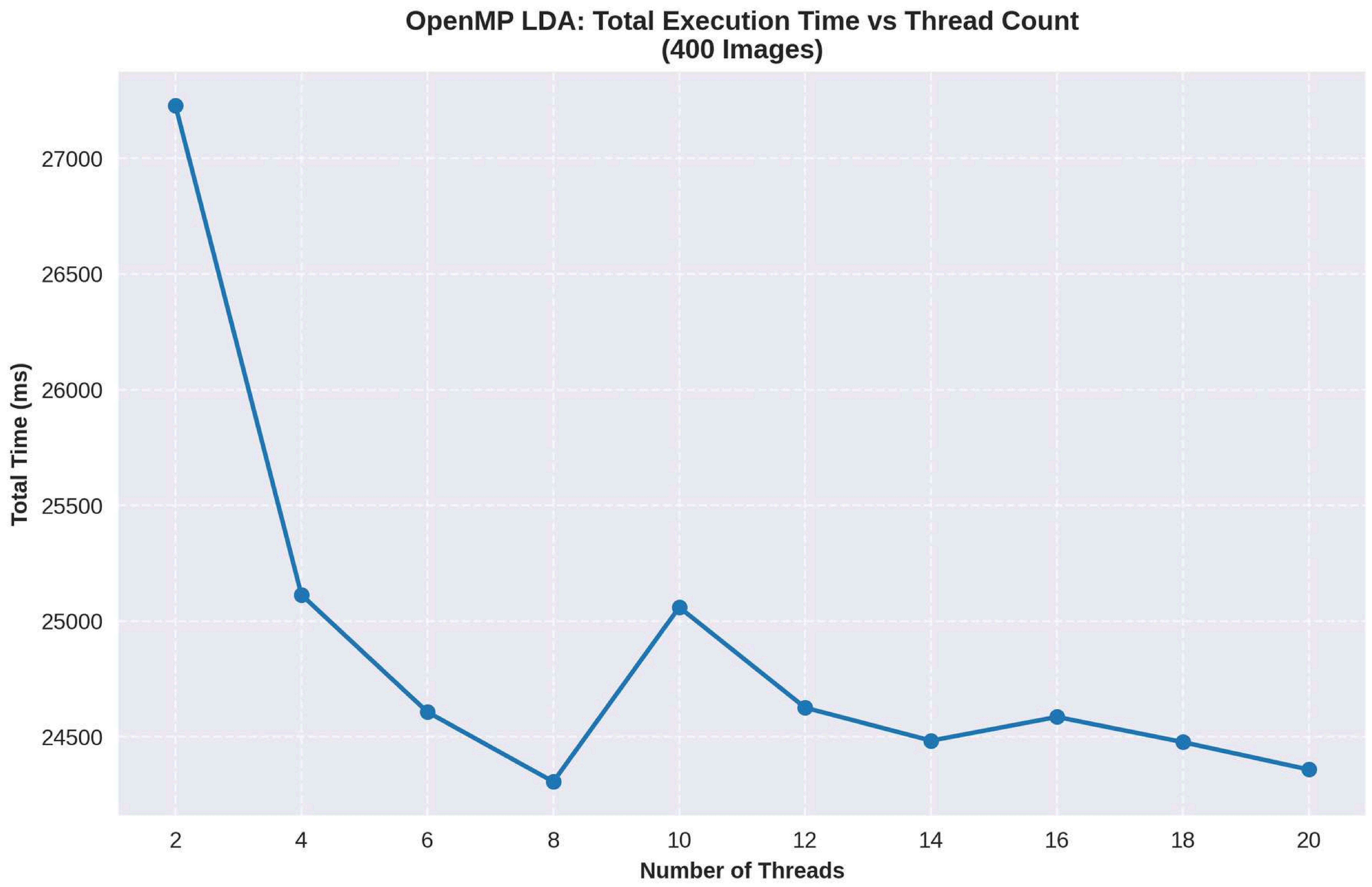
AREAS FOR PARALLELIZATION – LDA 3

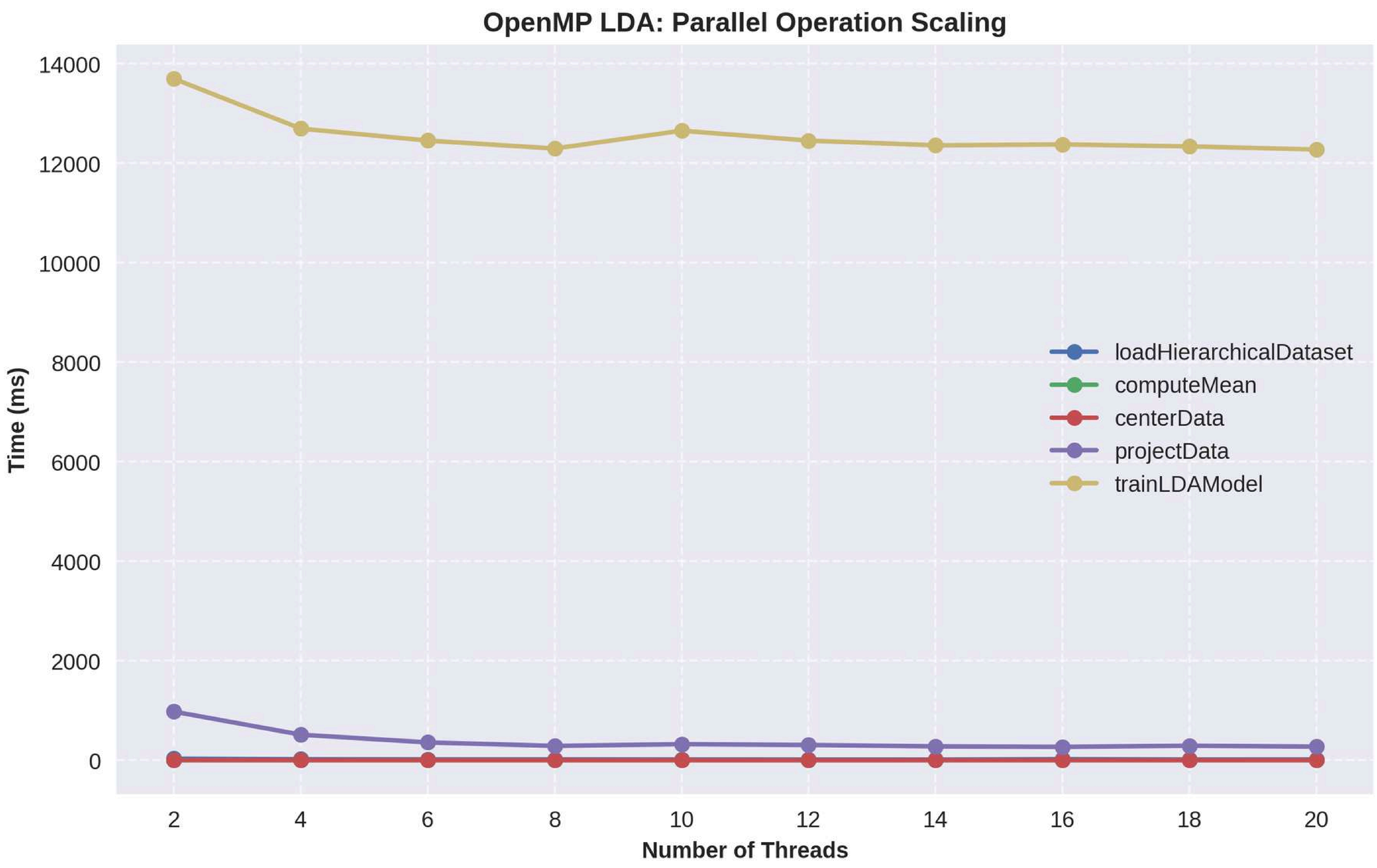
7. Projection onto Fisherfaces

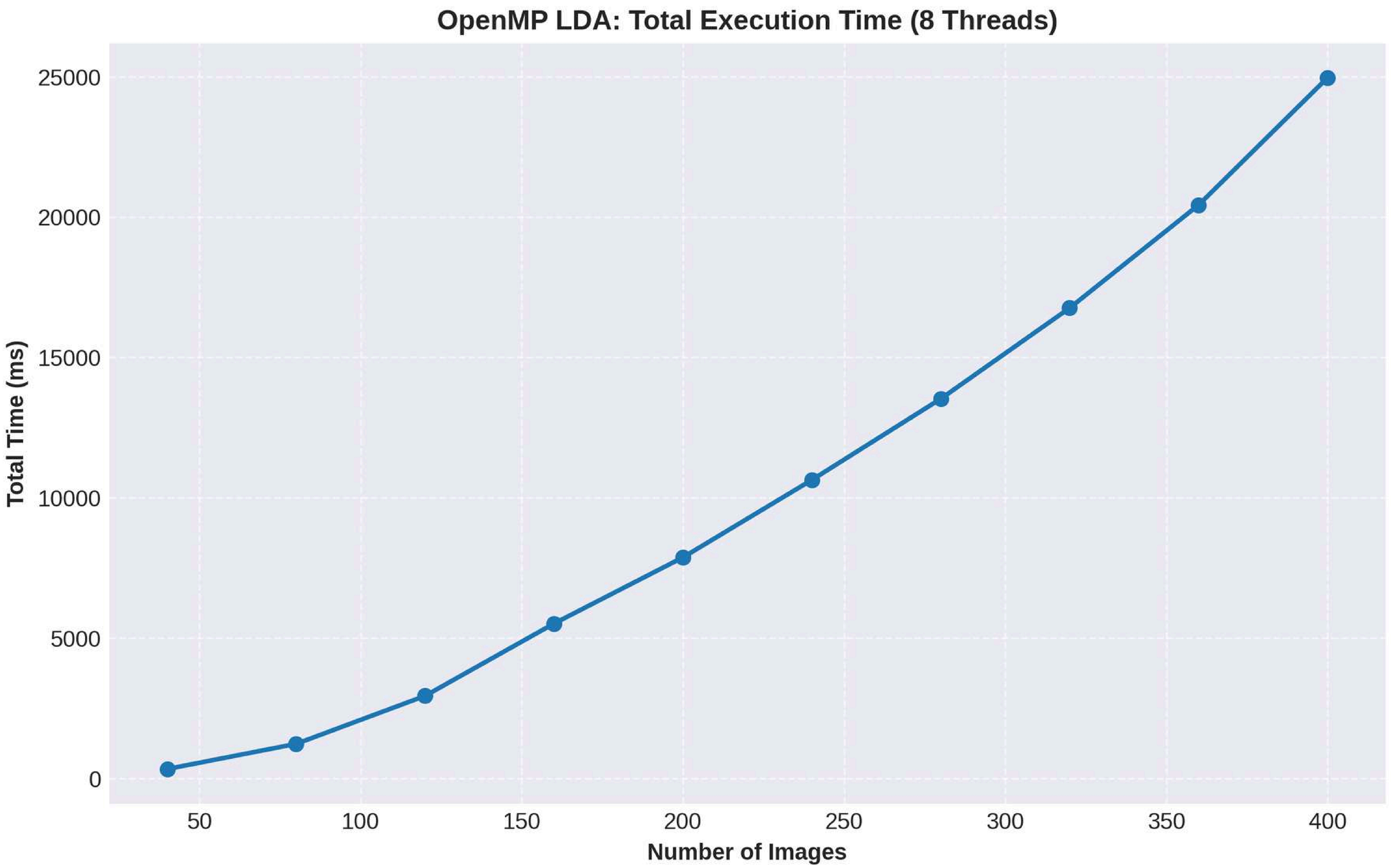
- Project the training and test data onto the Fisherfaces.
- Parallelization: Process each image independently during projection.

8. Reconstruction

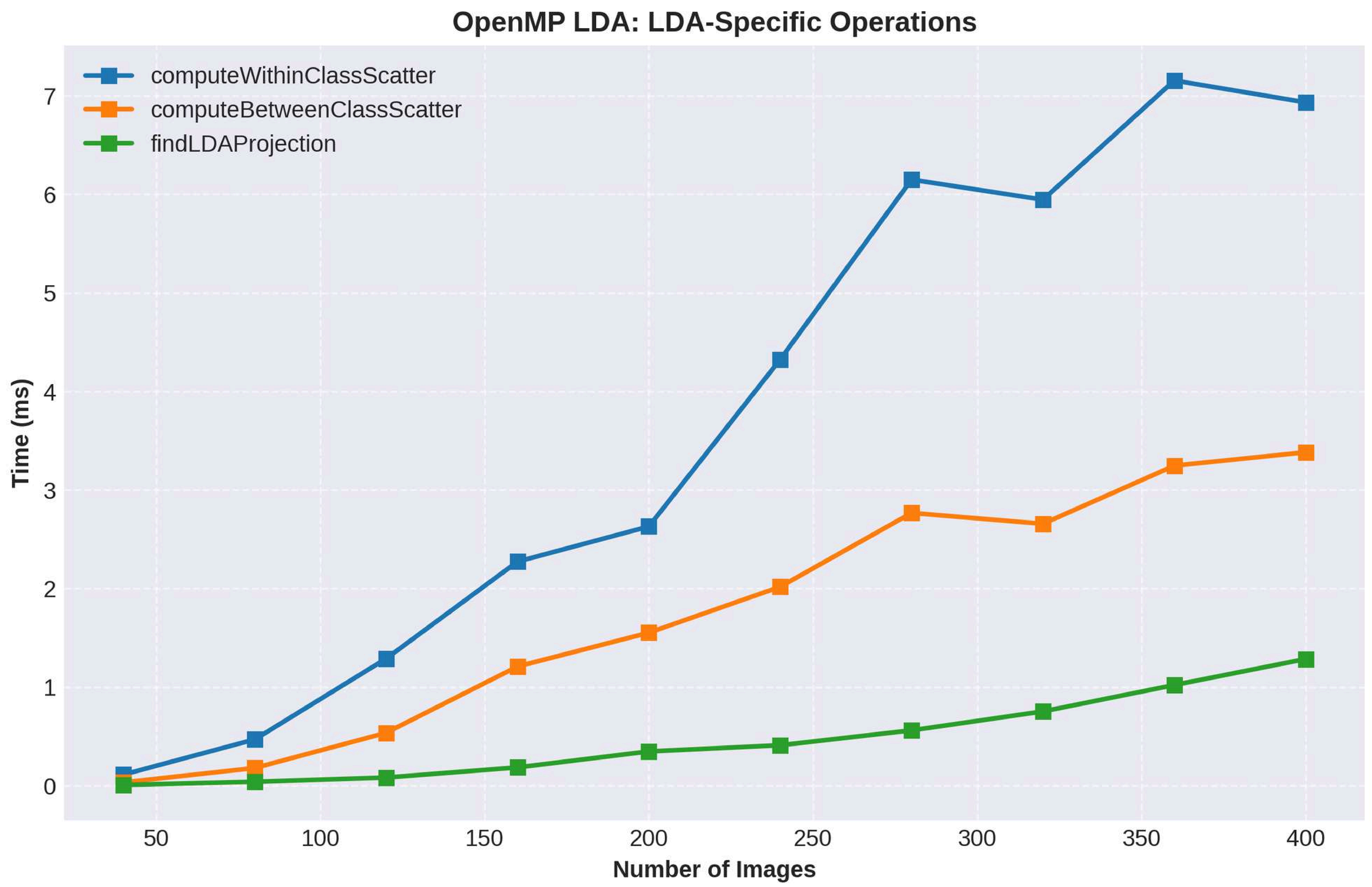
- Reconstruct images from their projections.
- Parallelization: Distribute reconstruction computations across threads or CUDA blocks.


OpenMP LDA: Total Execution Time vs Thread Count
(400 Images)
Total Time (ms)
27000
26500
26000
25500
25000
24500
2
4
6
8
10
12
14
16
18
20
Number of Threads

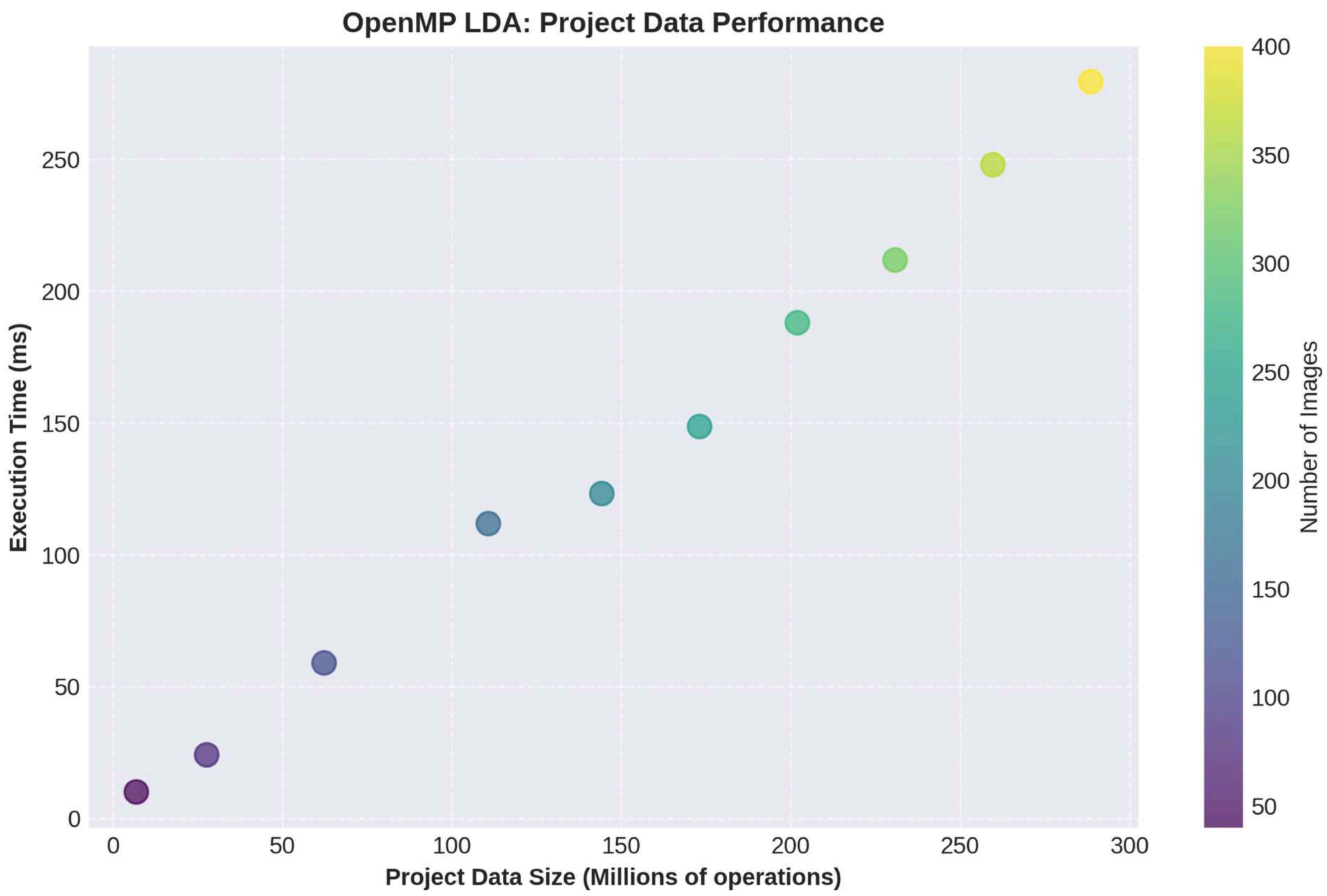

OpenMP LDA: Parallel Operation Scaling
Time (ms)
Number of Threads
0
2000
4000
6000
8000
10000
12000
14000
2
4
6
8
10
12
14
16
18
20
loadHierarchicalDataset
computeMean
centerData
projectData
trainLDAModel

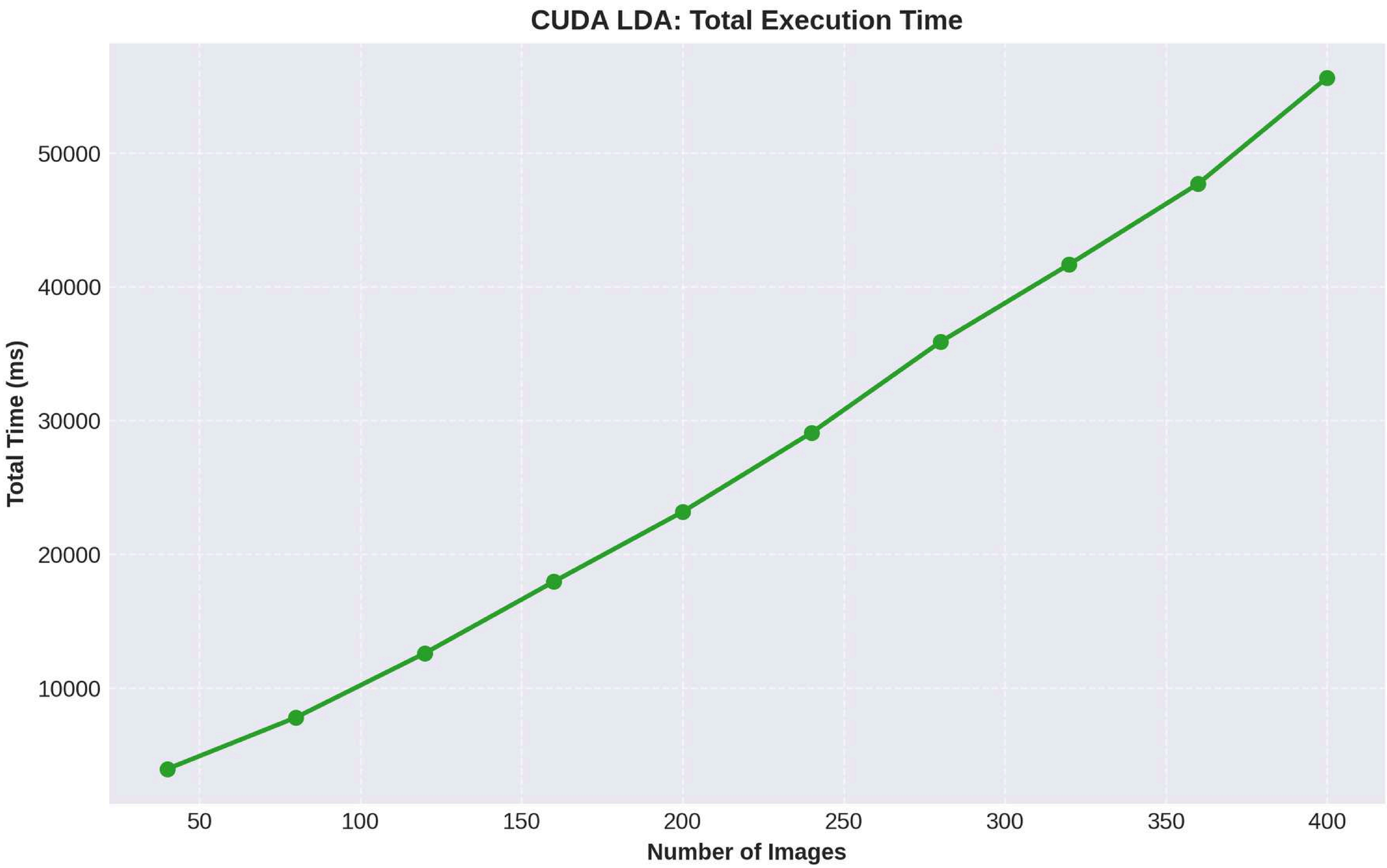


OpenMP LDA: Total Execution Time (8 Threads)
Total Time (ms)
0
5000
10000
15000
20000
25000
50
100
150
200
250
300
350
400
Number of Images

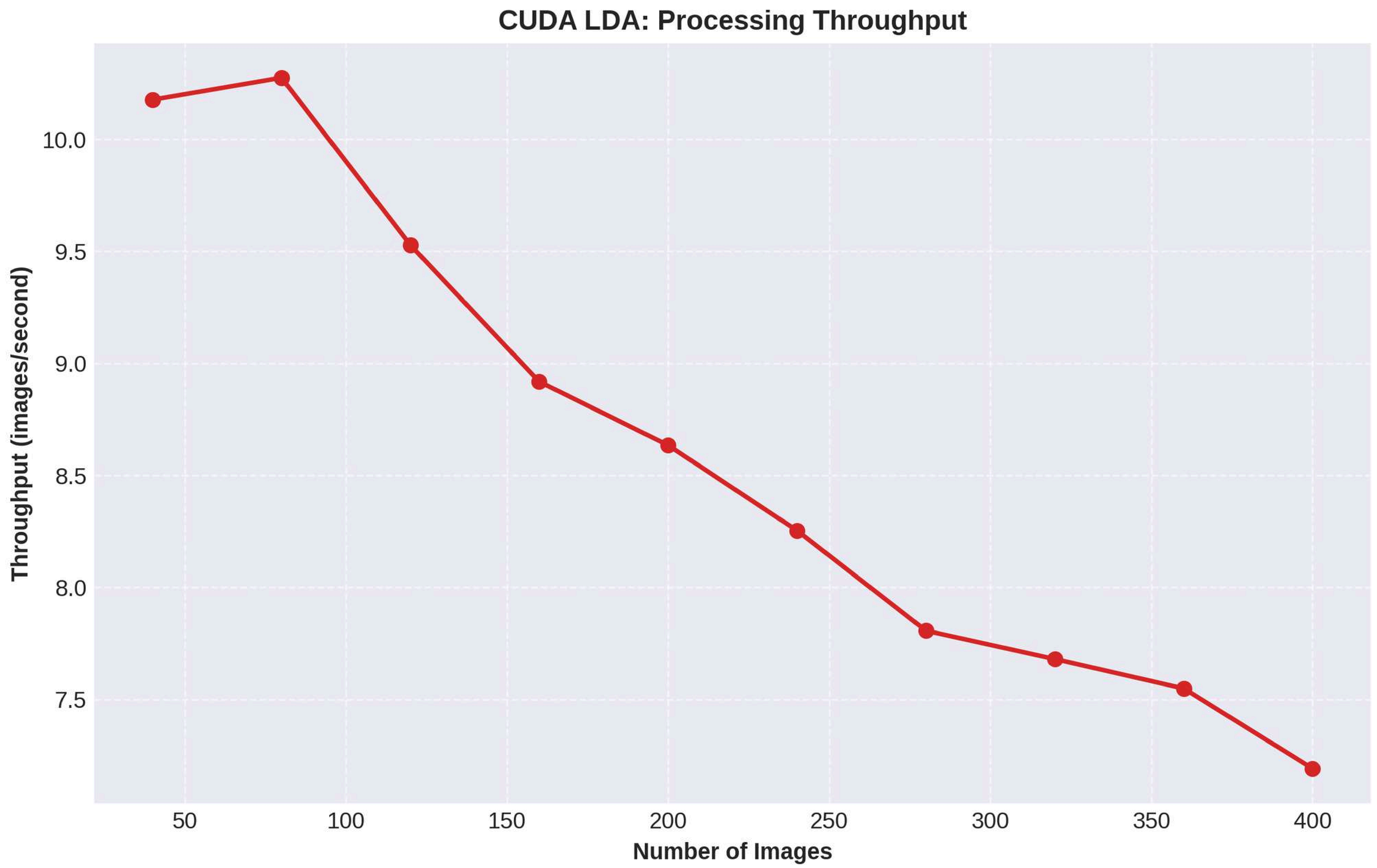


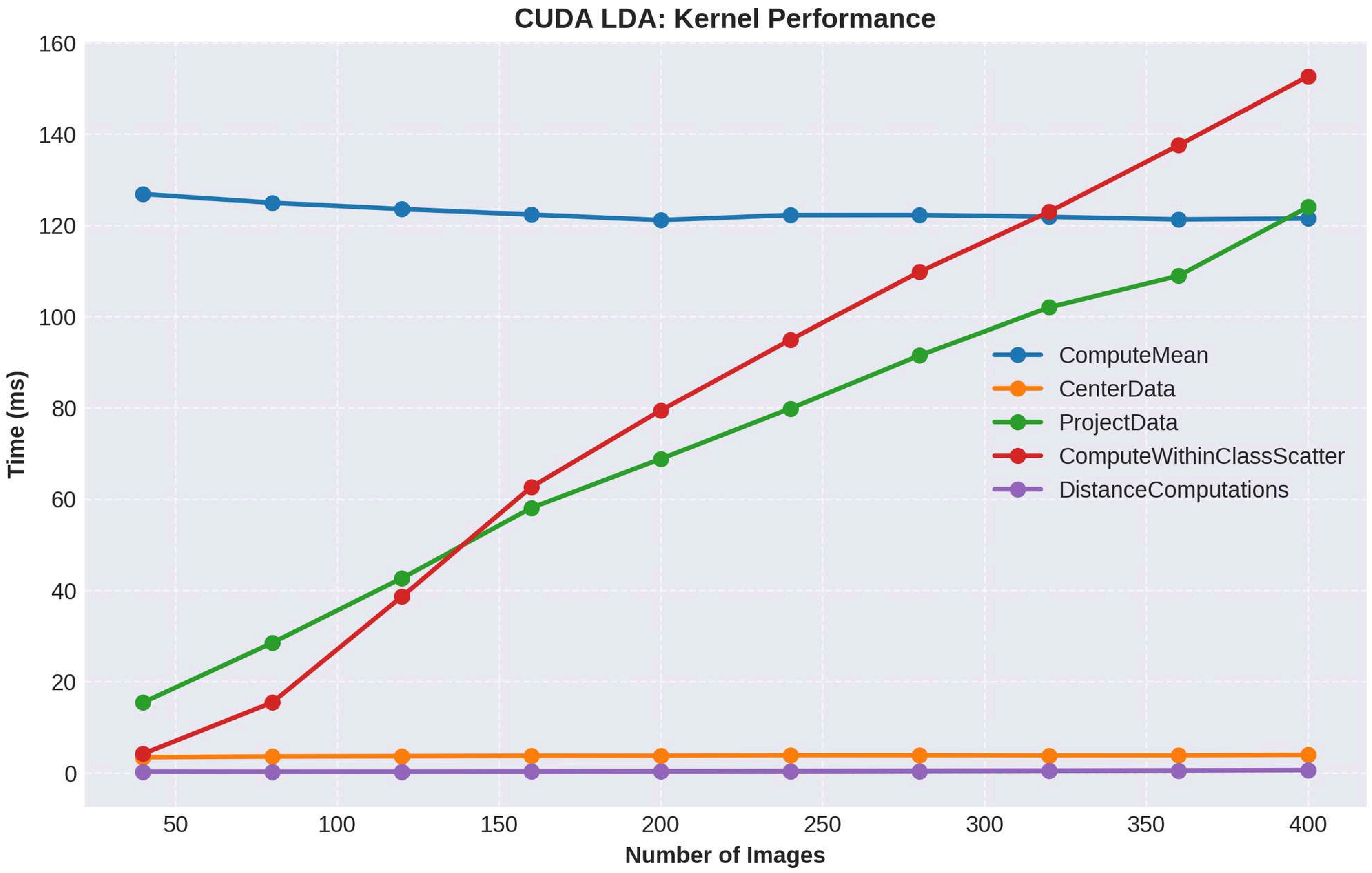
OpenMP LDA: LDA-Specific Operations
computeWithinClassScatter
computeBetweenClassScatter
findLDAProjection
Time (ms)
0
1
2
3
4
5
6
7
50
100
150
200
250
300
350
400
Number of Images

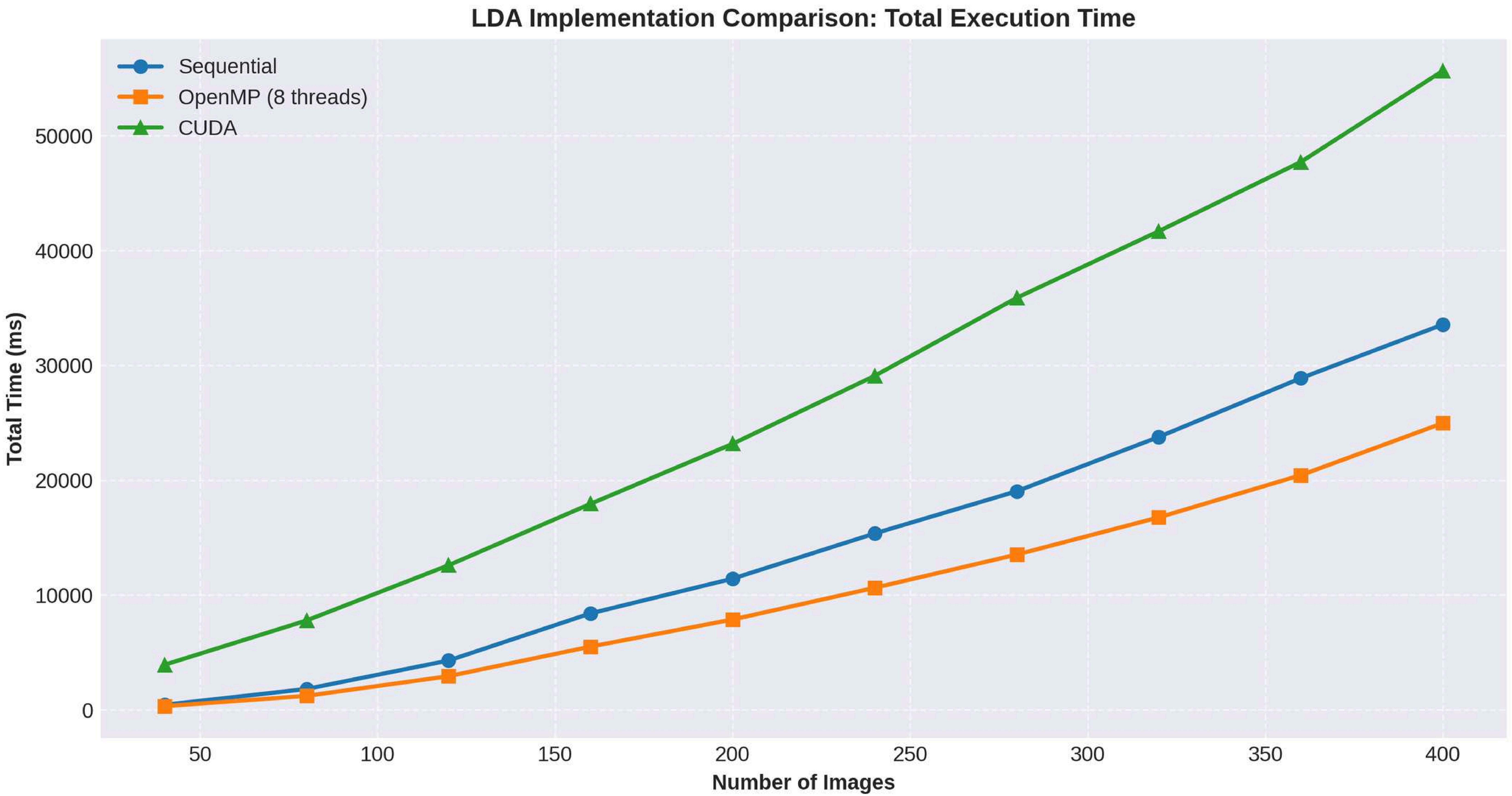

OpenMP LDA: Project Data Performance
Execution Time (ms)
0
50
100
150
200
250
0
50
100
150
200
250
300
Project Data Size (Millions of operations)
Number of Images
50
100
150
200
250
300
350
400



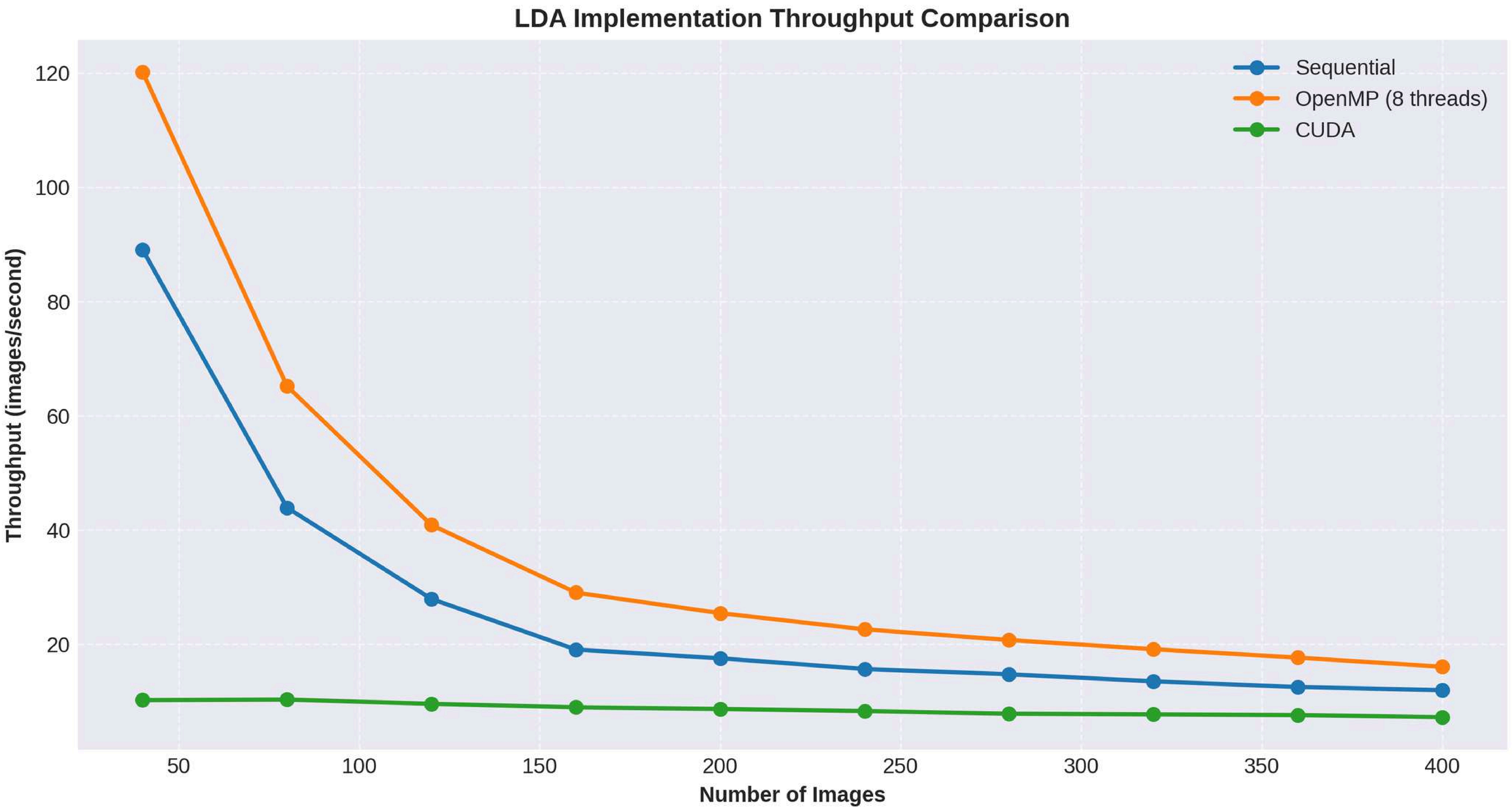
CUDA LDA: Total Execution Time
Total Time (ms)
50000
40000
30000
20000
10000
50
100
150
200
250
300
350
400
Number of Images


CUDA LDA: Processing Throughput
Throughput (images/second)
10.0
9.5
9.0
8.5
8.0
7.5
50
100
150
200
250
300
350
400
Number of Images

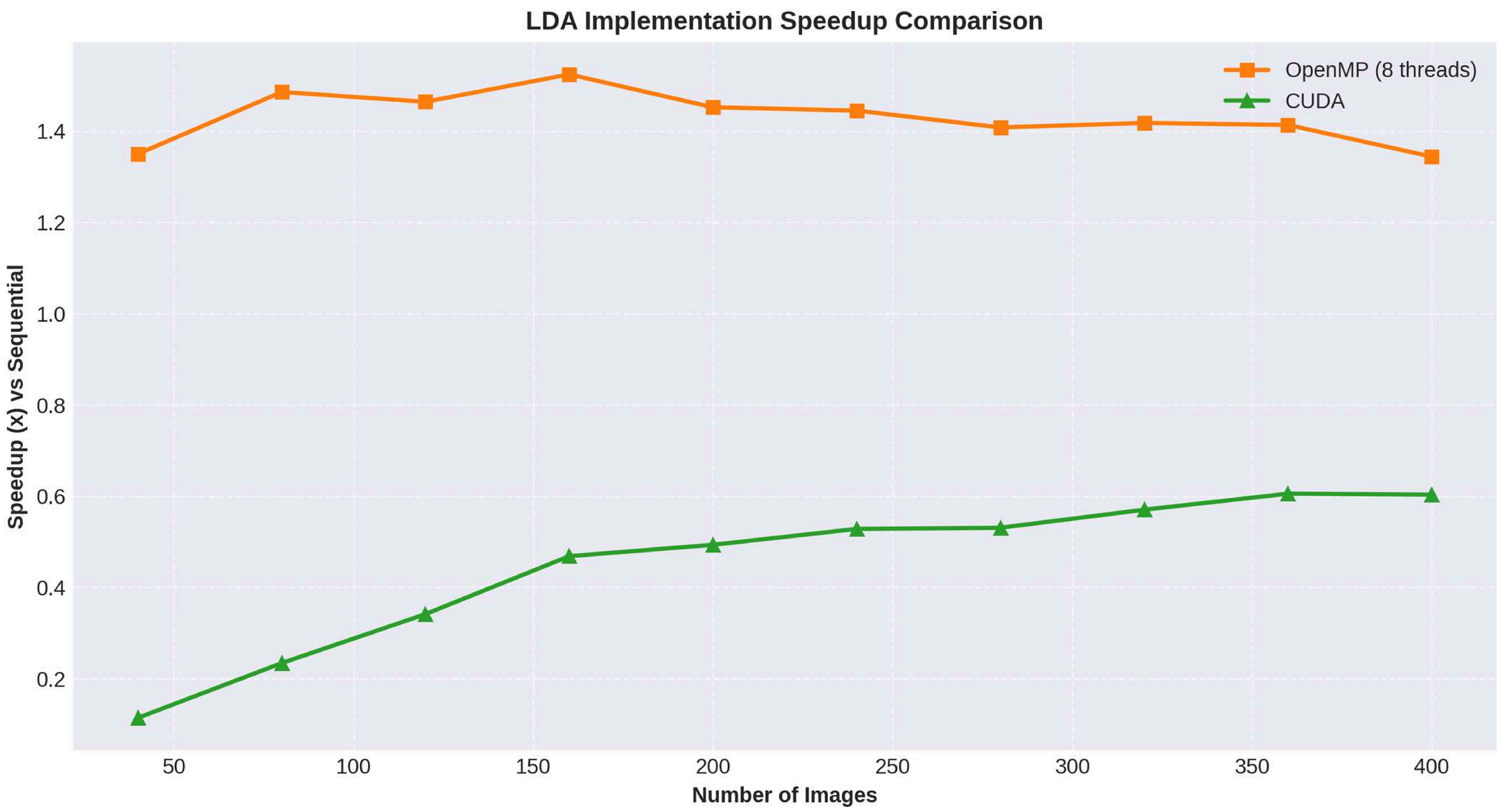

CUDA LDA: Kernel Performance
Time (ms)
Number of Images
0
20
40
60
80
100
120
140
160
50
100
150
200
250
300
350
400
ComputeMean
CenterData
ProjectData
ComputeWithinClassScatter
DistanceComputations



LDA Implementation Comparison: Total Execution Time
Sequential
OpenMP (8 threads)
CUDA
Total Time (ms)
0
10000
20000
30000
40000
50000
Number of Images
50
100
150
200
250
300
350
400



LDA Implementation Throughput Comparison
Sequential
OpenMP (8 threads)
CUDA
Throughput (images/second)
Number of Images
20
40
60
80
100
120
50
100
150
200
250
300
350
400


LDA Implementation Speedup Comparison
OpenMP (8 threads)
CUDA
Speedup (x) vs Sequential
Number of Images
1.4
1.2
1.0
0.8
0.6
0.4
0.2
50
100
150
200
250
300
350
400