5. Results & Error Analysis

5.1 Quantitative Results

The performance of the face recognition system was evaluated using both a classical LBPH-based approach and an embedding-based deep learning method. Evaluation was conducted on a representative subset of the test data to ensure efficient experimentation while preserving meaningful performance trends.

The LBPH-based model achieved reasonable accuracy under controlled conditions; however, its performance degraded noticeably under variations in illumination and partial occlusion. In contrast, the embedding-based approach demonstrated improved robustness, particularly in handling pose and lighting variations.

Confusion matrices were generated for both approaches to analyze classification behavior beyond aggregate accuracy metrics. These visualizations reveal distinct error patterns between classical and embedding-based methods, highlighting the strengths and limitations of each approach.

5.2 Confusion Matrix Analysis

Figure 1 presents the confusion matrix obtained from the LBPH-based face recognition experiments. The matrix indicates that while many identities are correctly classified, misclassifications increase under non-ideal conditions. Several off-diagonal entries suggest confusion between visually similar identities, especially when illumination changes or facial features are partially occluded.

Figure 2 shows the confusion matrix for the embedding-based approach. Compared to LBPH, this method exhibits fewer misclassifications overall and improved separation between identities. The reduction in off-diagonal errors indicates better generalization and robustness.

5.3 Error Patterns and Failure Modes

A detailed analysis of incorrect predictions highlights two primary error types: false positives and false negatives.

False positives occur when the system incorrectly identifies one individual as another. In attendance systems, this error is particularly critical, as it may result in incorrect presence marking, compromising data integrity and user trust. The LBPH model exhibited a higher false positive rate under challenging lighting conditions.

False negatives occur when the system fails to recognize a known individual. While less damaging than false positives in some contexts, repeated false negatives may lead to user frustration and reduced confidence in automated systems.

5.4 Human-Centered Impact of Errors

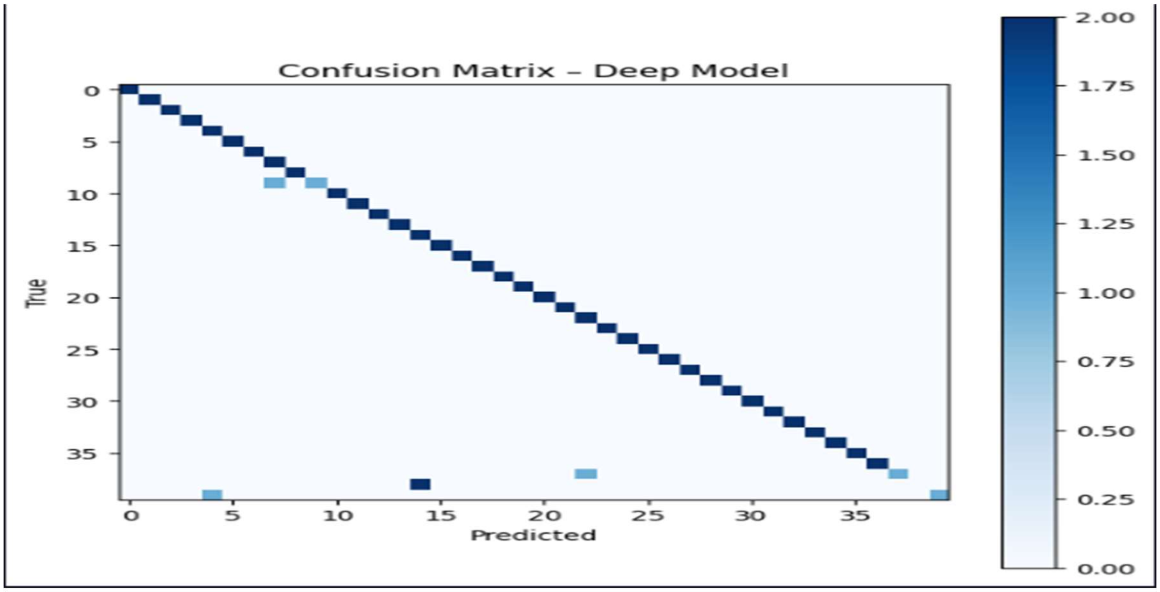
From a human-centered perspective, the impact of recognition errors extends beyond numerical performance metrics. In real-world attendance systems, false positives can unfairly benefit some users while disadvantaging others, raising concerns related to fairness and accountability.

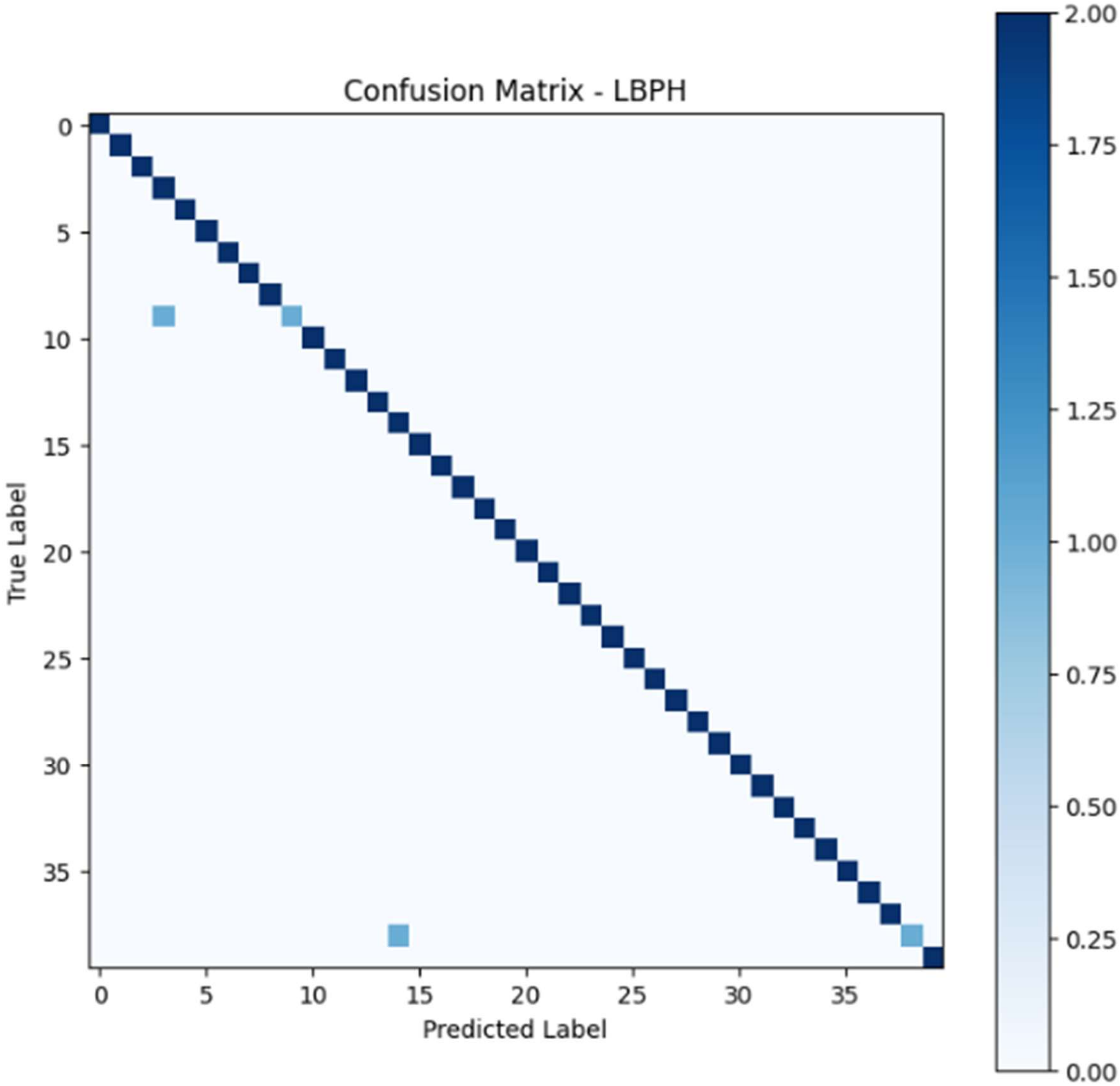
These findings emphasize the importance of prioritizing error types based on application context. For attendance management, minimizing false positives is particularly important to maintain trust and ensure ethical deployment.

5.5 Summary of Findings

Overall, the experimental results demonstrate that classical LBPH-based face recognition systems are effective under controlled conditions but lack robustness in real-world scenarios. Embedding-based approaches provide improved performance and reduced error rates, though challenges remain under extreme variations.

The error analysis highlights the necessity of combining technical robustness with human-centered considerations when deploying face recognition systems in practice.


Confusion Matrix – Deep Model
True
Predicted
0
5
10
15
20
25
30
35
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00


Confusion Matrix - LBPH
True Label
Predicted Label
0
5
10
15
20
25
30
35
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00