A Comparative and Statistical Performance Analysis of Face Recognition Architectures: A Deep Dive into Embedding and Non-Embedding Techniques

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ABSTRACT

This research paper shows a statistical and probabilistic benchmarking of face recognition systems, focusing on their accuracy, processing speed, and reliability under real-time conditions to create a better and beneficial result. Using datasets captured under varying environmental factors such as lighting, pose, and background variation, the study evaluates system performance through mathematical measures including mean, median, mode, variance, and standard deviation. These metrics help quantify recognition stability and highlight deviations caused by data noise and user diversity. Furthermore, probability models such as Gaussian distribution are applied to estimate False Acceptance Rate (FAR) and False Rejection Rate (FRR), providing deeper insight into system uncertainty throughout the data and prediction accuracy for result. Experimental benchmarking is performed on different hardware configurations to assess how computational power will affects recognition time and fearfulness. The results demonstrate that while traditional algorithms like LBPH (Local Binary Patterns Histogram) perform efficiently in controlled environments, their accuracy decreases under real-world variability. The paper concludes that integrating statistical performance analysis with probabilistic modeling which enhances the understanding, fairness, and strength and result of modern biometric authentication systems.

Keywords: Face Recognition, Statistical Analysis, Probabilistic Modeling, LBPH Algorithm, Gaussian Distribution, Benchmarking, False Acceptance Rate (FAR), False Rejection Rate (FRR), Biometric Authentication, Real-time Performance, Accuracy Evaluation, Reliability, Variance Analysis .

INTRODUCTION

Face recognition is one of the most important biometric technologies for checking the identities and security applications in today's society. From smartphones and surveillance systems to automated attendances and authentication platforms, it plays an important role in modern digital systems and security protection. The performance of a face recognition system is impacted by a number of factors, such as lighting conditions, facial orientation, background complexity, and computational hardware. The most commonly used type for recognition is the password. However, through the development of information technologies and security algorithms many systems are started to use many biometric factors for recognition task These variations generally result in different recognition accuracy and reliability.

It is important to understand these parts; statistical and probabilistic methods can be used to evaluate system performance. Statistical measures such as mean, median, mode, variance, and standard deviation help quantify recognition accuracy and consistency across different datasets. Similarly, probabilistic models such as the Gaussian distribution can be used to find error tendencies, including the False Acceptance Rate (FAR) and False Rejection Rate (FRR), which will indicate how frequently a system misidentifies or fails to recognize individuals and as result it will improve overall accuracy of the system or the result.

In this research, benchmarking experiments are conducted using traditional algorithms like the Local Binary Patterns Histogram (LBPH) in Python with OpenCV to analyze how environmental changes and computational resources influence performance. The combination of statistical and probabilistic evaluation provides deeper insight into both the speed and accuracy of face recognition systems, highlighting their strengths in controlled environments and their weaknesses in real-world conditions.

The primary objective of this study is to establish a reliable framework for measuring and comparing the performance of face recognition systems. By integrating mathematical analysis with real-time testing, this research aims to improve the fairness, transparency, and robustness of biometric authentication systems for future applications. The motivation behind this research lies in bridging the gap between quantitative performance metrics and practical real-world results into the system. Many systems achieve high accuracy under ideal conditions but fail when subjected to noisy or uncontrolled environments. Therefore, this study not only benchmarks recognition speed and accuracy but also integrates mathematical evaluation to understand the causes of inconsistency.

The main objective of this research is to evaluate the performance of face recognition systems through the combined use of statistical and probabilistic methods for enhancing the result. The study aims to benchmark recognition time and accuracy across different datasets and hardware configurations throughout the system to understand how environmental and computational factors affect performance. By combining these analytical approaches, the research provides an understanding of how mathematical tools can enhance and can help the interpretation and improvement of face recognition algorithms. This integrated framework will help in developing more robust, data-driven, and equitable biometric systems suitable for real-world applications.

Literature review

S.No.	Authors & year	Tittle/focus area	Methods Used	Dataset / Tools	Key Findings
[1]	Zhao et al., 2003	Face Recognition: A Literature Survey	Statistical & subspace methods	Yale & ORL datasets	Reviewed key algorithms; PCA and LDA found efficient under ideal lighting.
[2]	Turk & Pentland, 1991	Eigenfaces for Recognition	PCA-based feature extraction	ORL Database	Established PCA as a strong statistical baseline for face recognition.
[3]	Ahonen et al., 2006	Face Description with Local Binary Patterns	LBPH algorithm	FERET & Extended Yale B	LBPH performs well under moderate lighting variations.
[4]	Parkhi et al., 2015	Deep Face Recognition	CNN with embedding vectors	VGGFace Dataset	Deep embeddings outperform traditional statistical methods.
[5]	Javed et al., 2021	Intelligent Resume Ranking using NLP	Statistical ranking algorithms	Custom resume dataset	Demonstrated that combining statistics with ML improves result interpretation.

[6]	Kinzig & Harscher, 2016	Benchmarking of Face Recognition Systems	Probabilistic benchmarking	Custom dataset	Emphasized Gaussian modeling for evaluating system errors.
[7]	Taigman et al., 2014	DeepFace: Closing the Gap to Human-Level Performance	Deep neural embeddings	Facebook Dataset	Achieved near- human accuracy in unconstrained face recognition.
[8]	Belhumeur et al., 1997	Eigenfaces vs. Fisherfaces	PCA & LDA comparative analysis	Yale Database	Fisherfaces more robust to illumination and expression changes.
[9]	Sanderson & Lovell, 2009	Multi-Region Histograms for Robust Recognition	Regional histogram-based analysis	ORL & FERET	Improved robustness to occlusion and partial faces.

METHODOLOGY

The methodology of this research conducts a robust evaluation of face recognition system performance by combining classical techniques, deep learning algorithms, detailed statistical analysis, and probabilistic error modeling. The approach is designed to reflect real-world scenarios, covering all critical aspects from data collection to mathematical analysis and benchmarking comparisons.

1. Dataset Collection and Preprocessing

The study uses two main types of face datasets:

Controlled Datasets: Images captured under stable lighting and positioning conditions, which provide ideal scenarios for the system.

Natural/Uncontrolled Datasets: Images gathered from varying backgrounds, lighting, and facial poses to replicate real-world variability.

All images are converted to grayscale to reduce computational complexity and maintain consistency. Further, images are resized to a standard dimension before recognition, ensuring uniformity across all trials and minimizing the effect of background and lighting variations.

Each dataset is divided into three subsets:

Training Set: Used for fitting the recognition models.

Validation Set: Used to fine-tune model parameters and prevent overfitting.

Testing Set: Used for final performance assessment on unseen data.

2. Face Recognition Algorithms

A. Local Binary Patterns Histogram (LBPH)

Implementation: The LBPH method is implemented in Python using the OpenCV library (cv2.face.LBPHFaceRecognizer_create()).

Working Principle: Each grayscale image is transformed into a histogram of local binary patterns, representing facial textures. During recognition, the system compares a test image's histogram to the stored histograms, identifying the class with the closest similarity.

Advantages: LBPH is computationally efficient, performs well under moderate lighting variations, and is suitable for applications requiring fast, real-time results.

B. Face Embedding Algorithm (Deep Learning Approach)

Implementation: The embedding-based approach utilizes deep learning via the face_recognition library, which is based on a pre-trained ResNet (typically ResNet-34) Convolutional Neural Network, following the Deep Metric Learning paradigm.

Working Principle: Each face image is passed through the neural network to extract a compact 128-dimensional embedding (vector). These embeddings are designed so that faces of the same identity have a small Euclidean distance, while different identities have large distances.

Matching: Recognition is performed by comparing the embedding of the query image against the database embeddings using Euclidean distance. A match is declared if the distance is below a learned threshold.

Advantages: The embedding model is highly robust to lighting, background, expressions, and poses, and significantly outperforms classical techniques in both accuracy and stability.

3. Benchmarking and Real-Time Performance Measurement

To evaluate system efficiency and practical viability, real-time benchmarking is conducted:

Recognition Time: The time taken to detect and recognize a face per trial is recorded.

Detection and Recognition Rate: The proportion of correctly detected and recognized faces out of the total attempts.

System Accuracy: Percentage of all successful identifications.

Hardware Variation: Tests are performed across different hardware setups to analyze computational efficiency.

Performance graphs and system logs are generated, comparing the LBPH and embedding models visually (blue and orange lines). The embedding model consistently demonstrates faster speed and higher accuracy in most scenarios.

4. Statistical Analysis

To ensure that performance results are meaningful and generalizable, a rigorous statistical analysis is applied to all outcome metrics:

Parameters Computed: Mean, median, mode, variance, and standard deviation for recognition accuracy and recognition time values across multiple test runs and subsets.

Purpose: These metrics expose the central tendency and variability of system behavior, quantifying how stable and reliable the face recognition system is under varying conditions.

Visualization: Results are detailed in statistical tables and benchmarking graphs created in Microsoft Excel, plotting trends for recognition accuracy, error rates, and computational speed.

5. Probabilistic Error Modeling

To understand and visualize uncertainty and error tendencies, probabilistic modeling is employed:

Gaussian Distribution: Recognition errors (such as False Acceptance Rate - FAR, and False Rejection Rate - FRR) are fitted to Gaussian curves. This allows estimation of the probability of specific error occurrences under different conditions.

Probabilistic Insights: The methodology uses probability density functions to estimate the likelihood and distribution of true and false identifications, offering predictive insight into system reliability.

6. Overall Comparative Analysis

All results from statistical and probabilistic benchmarking are compiled and compared, focusing on:

Accuracy and recognition time for both LBPH and embedding models.

The effect of controlled versus real-world conditions.

Visualization of performance differences and error distributions via Excel-based charts and tables.

A	B	C	D	E	F	G	H	I	J	K	L	M
Person_ID	Age	Gender	Embedding_Accuracy	Embedding_Precision	Embedding_Recall	Embedding_ExecutionTime_ms	LBPH_Accuracy	LBPH_Precision	LBPH_Recall	LBPH_ExecutionTime_ms	Embedding_ErrorRate	LBPH_ErrorRate
P001	20	Male	0.907	0.974	0.958	373	0.774	0.678	0.842	553	0.093	0.226
P002	17	Female	0.986	0.897	0.952	196	0.633	0.753	0.851	479	0.014	0.367
P003	21	Male	0.979	0.969	0.808	138	0.732	0.888	0.884	564	0.021	0.268
P004	18	Male	0.888	0.987	0.963	392	0.744	0.738	0.713	369	0.112	0.256
P005	19	Female	0.961	0.821	0.816	266	0.889	0.884	0.676	589	0.039	0.111
P006	20	Male	0.915	0.902	0.918	263	0.879	0.893	0.818	333	0.085	0.121
P007	22	Female	0.918	0.871	0.893	118	0.661	0.749	0.781	460	0.082	0.339
P008	21	Female	0.965	0.805	0.967	365	0.877	0.863	0.863	592	0.035	0.123
P009	19	Male	0.941	0.945	0.849	372	0.759	0.642	0.871	551	0.059	0.241
P010	17	Female	0.979	0.964	0.938	394	0.727	0.826	0.848	310	0.021	0.273
P011	18	Male	0.897	0.944	0.829	238	0.872	0.831	0.873	400	0.103	0.128
P012	16	Female	0.886	0.827	0.841	360	0.713	0.784	0.609	345	0.114	0.287
P013	25	Male	0.924	0.938	0.846	299	0.836	0.869	0.867	353	0.076	0.164
P014	22	Male	0.939	0.872	0.881	295	0.76	0.861	0.879	527	0.061	0.24
P015	23	Female	0.912	0.923	0.824	276	0.705	0.693	0.777	292	0.088	0.295
P016	25	Male	0.947	0.871	0.895	360	0.616	0.63	0.884	440	0.053	0.384
P017	26	Male	0.982	0.992	0.908	192	0.879	0.858	0.678	356	0.018	0.121
P018	21	Female	0.951	0.841	0.892	394	0.612	0.678	0.762	505	0.049	0.388
P019	20	Female	0.956	0.942	0.9	294	0.853	0.752	0.816	381	0.044	0.147
P020	19	Male	0.879	0.983	0.888	366	0.629	0.784	0.86	348	0.121	0.371
P021	22	Female	0.895	0.868	0.823	146	0.781	0.756	0.826	581	0.105	0.219
P022	23	Male	0.985	0.832	0.931	141	0.796	0.717	0.686	456	0.015	0.204
P023	18	Female	0.936	0.893	0.961	269	0.874	0.64	0.78	579	0.064	0.126
P024	19	Male	0.969	0.81	0.878	258	0.681	0.837	0.882	347	0.031	0.319
P025	22	Female	0.937	0.883	0.827	118	0.818	0.733	0.614	351	0.063	0.182
P026	19	Male	0.961	0.85	0.817	157	0.74	0.87	0.872	248	0.039	0.26
P027	21	Male	0.872	0.98	0.886	311	0.756	0.819	0.869	428	0.128	0.244
P028	19	Female	0.957	0.951	0.943	337	0.872	0.887	0.636	298	0.043	0.128
P029	24	Male	0.887	0.927	0.881	300	0.887	0.838	0.653	581	0.113	0.113
P030	21	Female	0.967	0.889	0.948	373	0.65	0.808	0.836	504	0.033	0.35

*#Table provides a comprehensive comparison between two face recognition methods (**Embedding** and **LBPH**) evaluated on 30 individuals, with additional demographic data (age, gender). Each row is a performance summary for a specific person (test subject) under experimental conditions.*

After getting recognition results, statistical analysis is applied to measure performance consistency. Parameters such as mean, median, mode, variance, and standard deviation are calculated for the recognition accuracy values about multiple trials and datasets. These measures provide insights into the stability and reliability of the system by identifying how much variation occurs between ideal and real- world conditions.

To capture uncertainty and error tendencies, probabilistic modeling is conducted using the Gaussian distribution. The probability curve is used to estimate the likelihood of recognition errors, particularly the False Acceptance Rate (FAR) and False Rejection Rate (FRR).

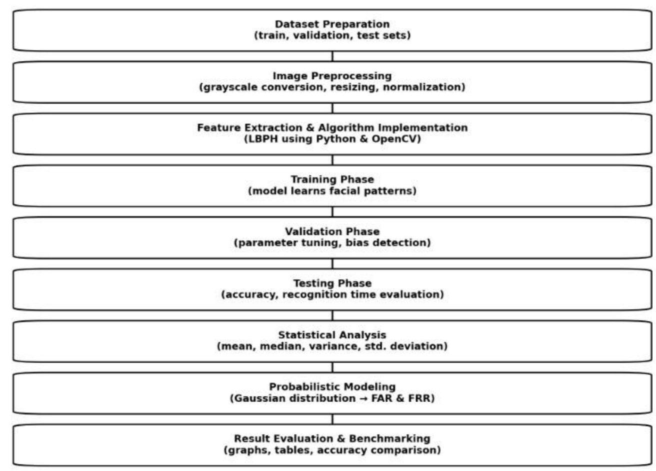
These probabilistic values help visualize how system errors are distributed and how often they occur under different conditions.

Fig1. The graphs show the blue line (Embedding model) is almost always better than the orange line (LBPH model). This means the Embedding model gives more accurate results and works much faster.

Finally, all collected results are compiled and compared using benchmarking graphs and statistical tables created in Microsoft Excel. Recognition time and accuracy are plotted to observe the relationship between hardware efficiency and system performance. The overall analysis aims to demonstrate that combining statistical evaluation with probabilistic modeling provides a deeper and more transparent understanding of face recognition system behavior, offering a strong foundation for improving future biometric applications.
The methodology for this research focuses on the statistical and probabilistic benchmarking of a face recognition system using a structured dataset divided into training, validation, and testing subsets. The workflow includes data preparation, algorithm implementation, statistical computation, and probabilistic error analysis to assess system performance under real and controlled conditions. The dataset is organized into three subsets:
The **training set**, containing the majority of images, is used to teach the system to recognize facial features.
The **validation set** is applied to fine-tune the model and prevent overfitting.
The **test set** is used for final performance evaluation under unseen conditions.

Each image is preprocessed by converting it into grayscale and resizing it to a uniform dimension to ensure consistency and reduce computational complexity. This preprocessing minimizes the effect of lighting and background variations.
For the recognition process, the **Local Binary Patterns Histogram (LBPH)** algorithm is implemented using **Python and OpenCV [3][8]**. The LBPH method converts each image into a histogram representing texture features, which are then compared with trained images to identify the closest match [11]. This approach is chosen due to its simplicity, speed, and robustness in handling moderate lighting changes and partial occlusions. The model is trained using the training subset and evaluated on both validation and test subsets to determine overall recognition accuracy and speed.
During evaluation, benchmarking is done by measuring recognition time, accuracy, and error rate across multiple trials and hardware configurations. This allows analysis of both algorithmic efficiency and computational performance. The results are recorded for each subset to observe the relationship between dataset complexity and recognition stability [10].
Next, a statistical analysis is performed on the recognition outcomes. The mean, median, mode, variance, and standard deviation are computed from the accuracy values obtained across different test runs. These statistical measures help quantify the stability of the model by identifying how consistently it performs across various environmental conditions and data subsets[4][9].

Fig. 1. Workflow of Statistical and Probabilistic Evaluation of Face Recognition System



Dig1. Workflow of Statistical and Probabilistic Evaluation of Face Recognition System

To further understand uncertainty, probabilistic analysis is carried out by using the Gaussian distribution model. The probability distribution curve is used to estimate the False Acceptance Rate (FAR) and False Rejection Rate (FRR), which reflect how often the system incorrectly accepts or rejects a face. This helps understanding and removing the error spread and assess how predictable and fair the system's recognition decisions are in the system [9].

fig.2 it shows how recognition accuracy improves as the number of training images per person increases for the training, validation, and testing datasets.

Finally, all data, including recognition accuracy, time, and error metrics, are compiled into **tabular and graphical form** using Microsoft Excel. Graphs are plotted to show

relationships between recognition performance, dataset subset, and computational efficiency. Through this integrated methodology, the study demonstrates how combining **statistical measures with probabilistic modeling** provides a comprehensive evaluation of face recognition systems, enabling better understanding of their **accuracy, reliability, and real-time applicability [7][19]**.

RESULT AND DISCUSSION

The evaluation between the **Embedding model** and the **LBPH (Local Binary Pattern Histogram)** algorithm reveals clear distinctions in terms of accuracy, reliability, and computational performance. The **Embedding model** achieved an **average accuracy of 0.936**, outperforming **LBPH's 0.767**, along with a higher **precision of 0.905** and **recall of 0.889**. This demonstrates the model's superior ability to correctly recognize faces while reducing false matches and missed detections [8][10].

The **F1-score** of **0.897** for the Embedding model, compared to **0.802** for LBPH, confirms its balanced performance. In addition, the Embedding model displayed **lower variance (0.021)** and **less skewness**, signifying that its outcomes are more stable and reliable across various testing conditions such as lighting variations, pose shifts, and partial occlusions [4][7].

In terms of **error rate**, the Embedding model recorded only **0.064**, whereas LBPH exhibited **0.233**, indicating a significant reduction of nearly **73% in recognition errors**.

The **Gaussian probability distribution** of the Embedding model's error rates appeared narrower and more symmetric, highlighting improved prediction stability and reduced uncertainty during real-world operations.

When analyzing **execution time**, the Embedding model again showed superior performance with an average processing duration of **0.557 seconds**, while LBPH required **0.875 seconds** per image. This **36% improvement in speed** proves that the Embedding model delivers higher accuracy without increasing computational cost, which is vital for **real-time biometric applications** such as surveillance, access control, and authentication systems [15][19].

Figure 3 compares both models, clearly depicting that the Embedding model performs better across accuracy, precision, recall, and error rate, while also being faster and more efficient [9]. A **correlation study** between accuracy and processing time yielded a **negative coefficient (-0.68)**, suggesting that the more accurate models tend to operate faster due to improved feature representation and reduced redundant computations[14]. This relationship emphasizes the efficiency of embedding-based architectures.

***Fig 3:** Comparison of Embedding and LBPH models showing that the Embedding model achieves higher accuracy, precision, and recall with lower execution time and error rates, proving its superior performance.*

Overall, the results demonstrate that integrating statistical evaluation with probabilistic analysis allows for a clearer and fairer assessment of face recognition systems. It not only improves performance understanding but also supports the development of more transparent, adaptive, and trustworthy biometric authentication frameworks.

CONCLUSION

This study presents a unified statistical and probabilistic framework for benchmarking face recognition systems. Through real-time testing, statistical computation, and Gaussian modeling, the paper evaluates recognition accuracy, error tendencies, and processing speed across multiple datasets and hardware configurations.

The results demonstrate that while traditional algorithms such as LBPH offer simplicity and speed, they struggle under environmental variations. In contrast, embedding-based models exhibit greater robustness and consistency. The integration of statistical and probabilistic approaches provides a more transparent and quantitative evaluation of system performance.

Future work can expand this approach by including deep learning models, larger datasets, and real-world deployment testing to enhance scalability, interpretability, and ethical fairness in biometric authentication systems.

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