A COMPREHENSIVE COMPARATIVE STUDY OF TRADITIONAL MACHINE LEARNING CLASSIFIERS AND DEEP NEURAL ARCHITECTURES FOR FACE RECOGNITION

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Abstract. This study compares traditional face recognition methods (KNN, SVM, Random Forest) with modern DeepFace. Systems were implemented using these algorithms on datasets simulating real-world conditions. Results show traditional methods are simple to implement but lack speed and precision. DeepFace, leveraging deep learning, outperformed them with faster, more accurate recognition. The trade-off highlights the superiority of deep learning. Despite higher resource demands, it proves more effective for contemporary applications.

Keywords: Face Recognition, k-nearest neighbors (knn), support vector machines (svm), random forest, decision tree, deepface, machine learning, computer vision, biometric authentication, deep learning.

Аннотация. В этом исследовании сравниваются традиционные методы распознавания лиц (KNN, SVM, Random Forest) с современными методами DeepFace. Системы были реализованы с использованием этих алгоритмов на наборах данных, имитирующих реальные условия. Результаты показывают, что традиционные методы просты в реализации, но им не хватает скорости и точности. DeepFace, использующий глубокое обучение, превзошел их по скорости и точности распознавания. Этот компромисс подчеркивает превосходство глубокого обучения. Несмотря на более высокие требования к ресурсам, оно оказывается более эффективным для современных приложений.

Ключевые слова: распознавание лиц, k-число ближайших соседей (knn), метод опорных векторов (svm), случайный лес, дерево решений, deepface, машинное обучение, компьютерное зрение, биометрическая аутентификация, глубокое обучение.

Annotatsiya. Ushbu tadqiqot yuzni aniqlashning an’anaviy usullarini (knn, svm, random forest) zamonaviy deepface usullari bilan taqqoslaydi. Tizimlar ushbu algoritmlar yordamida real sharoitlarni taqlid qiluvchi ma’lumotlar to‘plamlarida amalga oshirildi. Natijalar shuni ko‘rsatadiki, an’anaviy usullarni amalga oshirish oson, ammo ular tezlik va aniqlikka ega emas. Chuqur o’rganishni qo’llagan DeepFace ularni tanib olish tezligi va aniqligi bo‘yicha ortda qoldirdi. Ushbu murosa chuqur o‘rganishning ustunligini ta’kidlaydi. Resurslarning yuqori talablariga qaramay, u zamonaviy ilovalar uchun samaraliroq bo’lib chiqadi.

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Kalit so‘zlar: yuzni aniqlash, k eng yaqin qo’shnilar (knn), vektorli mashinalar (svm), tasodifiy o’rmon, qaror daraxti, deepface, mashinali o’qitish, kompyuter ko’rish, biometrik autentifikatsiya, chuqur o’qitish.

Introduction

In the swiftly changing realm of artificial intelligence and computer vision, face recognition technology has become a fundamental element of contemporary digital systems. By 2025, facial recognition is essential for uses that span biometric security in smartphones and airports to customized user experiences in social media and healthcare diagnostics. The worldwide market for facial recognition is expected to surpass $15 billion by 2027, fueled by advancements in artificial intelligence and growing needs for contactless verification due to privacy issues and cybersecurity risks. Nonetheless, the efficacy of these systems depends on the foundational algorithms, which need to strike a balance between accuracy, speed, and resilience to challenges such as changing lighting, poses, and obstructions. This comparative examination analyzes conventional techniques—K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and Decision Tree—against a contemporary deep learning method, DeepFace, to assess their advantages, drawbacks, and appropriateness for practical face recognition applications.[1][2]

Conventional approaches embody essential machine learning techniques that depend on feature extraction and pattern recognition without the computational demands of deep neural networks. KNN is an instance-based, non-parametric algorithm that classifies a query face by assessing its similarity (e.g., Euclidean distance) to the k nearest labeled instances in the feature space. It is straightforward and user-friendly, making it suitable for small datasets; however, it is susceptible to noise and high dimensional attributes, where the "curse of dimensionality" may hinder performance.

SVM, a classic strong method, creates hyperplanes in high-dimensional spaces to distinguish classes with optimal margins, frequently utilizing kernel tricks (like RBF kernel) to manage non-linear data. In face recognition, SVM is adept at identifying distinguishing boundaries among facial features, providing robust generalization; however, it necessitates precise adjustment of parameters such as C (regularization) and may be resource-intensive for extensive datasets.[3][8]

Random Forest constructs a collection of decision trees, each developed from bootstrapped portions of data, and combines predictions through majority voting. This approach diminishes overfitting by incorporating randomness in feature selection and bagging, ensuring strong performance in face recognition by identifying varied patterns throughout the trees. It also provides insights on feature importance, helpful for pinpointing essential facial landmarks.[4]

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The Decision Tree, fundamental to Random Forest, constructs a hierarchical decision model by utilizing feature splits that aim to maximize information gain or reduce Gini impurity. In face recognition, it can divide data based on features such as the distance between eyes or the shape of the nose, but individual trees tend to overfit and become unstable with minor data variations.

Conversely, DeepFace represents contemporary methods by utilizing convolutional neural networks (CNNs) for comprehensive learning. DeepFace, generates deep embeddings from facial images, employing methods like triplet loss to position similar faces closer together in embedding space. This allows for improved precision in difficult circumstances, like low resolution or variations in pose, but requires substantial computational power and extensive labeled datasets for training.[5][7]

This analysis emphasizes the compromises: conventional techniques such as KNN and SVM are effective and understandable for basic situations, whereas ensembles like Random Forest enhance robustness, and deep strategies like DeepFace excel in accuracy for intricate, real-world scenarios. Through the evaluation of their performance on benchmarks such as LFW (Labeled Faces in the Wild) or specialized datasets, we seek to offer insights into choosing the right approach considering resource limitations, data volume, and necessary accuracy, thus informing future progress in biometrics and AI-enhanced security.[6]

METHODS

This study presents a comparative analysis of traditional and modern face recognition methods, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and DeepFace. The comparison is based on accuracy, computational efficiency, and performance on a well-known benchmark dataset.

The experiments were conducted using the LFW-Deep Funneled dataset, a refined version of the original Labeled Faces in the Wild (LFW). The dataset has a total size of 239 MB and includes 1,680 classes (individuals), filtered to ensure that each person has a minimum of 2 images. The images are stored in .jpeg / .jpg format and were preprocessed into 512-dimensional float32 vectors, representing face embeddings.

This embedding format allows for standardized input across all models and ensures computational efficiency, especially for traditional algorithms that cannot directly process raw images. Prior to model training and evaluation, all images were: Aligned and normalized using the Deep Funneled preprocessing pipeline. Converted to 512-dimensional face embeddings, using a pre-trained model to extract meaningful facial features. Filtered to remove identities with fewer than 2 images to ensure a fair classification setup.The resulting embeddings were used

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directly as input features for KNN, SVM, and Random Forest classifiers, while DeepFace was used as a modern deep learning baseline.

K-Nearest Neighbors (KNN): A non-parametric classification algorithm where a sample is assigned the most common label among its k nearest neighbors in the embedding space. The optimal value of k was determined using cross-validation.

For a test sample x, the predicted class y is given by:

$$y = argmax \sum_{i \in N_k(x)} II(y_i = c) \quad (1)$$

$N_k(x)$ — the set of k nearest neighbors of x,

II— indicator function (1 if y_i=c, else 0).

Support Vector Machine (SVM): A supervised learning method that finds the optimal hyper plane separating different classes. We tested both linear and RBF kernels, with hyper parameter tuning (C, gamma) via grid search.

For the linear case, the decision function is defined as:

$$f(x)=sign(w^T x + b) \quad (2)$$

The optimization problem is expressed as:

$$\min_{w,b} \frac{1}{2} ||w||^2 \ subject\ to\ y_i(w^T x_i + b) \geq 1 \quad (3)$$

$w^T x$—dot product,

b—bias, offset.

Random Forest: An ensemble of decision trees trained on subsets of the data and features. The number of estimators (trees), maximum tree depth, and minimum samples per leaf were optimized to balance bias and variance.

$$y = argmax \sum_{t=1}^{T} II(h_t(x) = c) \quad (4)$$

T — number of trees,

h_t(x) — prediction from the

The model reduces overfitting and improves generalization by combining multiple decision trees.

DeepFace: A deep learning-based framework for face recognition that uses convolutional neural networks to detect, align, and generate embeddings for face comparison. In this study, we used DeepFace both for embedding generation and for end-to-end identity classification using its built-in classification models.

Each image I is transformed into a low-dimensional embedding vector f(I)$\in R^{512}$.

Similarity between two faces I_1 and I_2 is computed using **cosine similarity**:

$$sim(I_1, I_2) = \frac{f(I_1) \cdot f(I_2)}{||f(I_1)||\ ||f(I_2)||} \quad (5)$$

Two faces are considered the same identity if:

$$sim(I_1, I_2) > \tau \quad (6)$$

where τ is a predefined similarity threshold.

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To assess and compare model performance, the following metrics were used: Accuracy: Proportion of correctly predicted identities. Precision, Recall, F1-score: Especially important due to class imbalance. Confusion Matrix: To analyze per-class performance and common misclassifications. Training and Inference Time: Used to evaluate computational efficiency and scalability of each model.

All experiments were implemented in Python using libraries such as scikit-learn for traditional models and DeepFace for deep learning-based recognition. Computations were conducted on a machine with the following specifications:
CPU: [Intel Core i6 / AMD Ryzen],
GPU: [NVIDIA RTX 3060 / None if not used],
RAM: [8 GB].

The models were trained and tested on the 512-dimensional embedding vectors. A stratified split (70% training, 30% testing) ensured that all individuals in the dataset were fairly represented across both subsets.

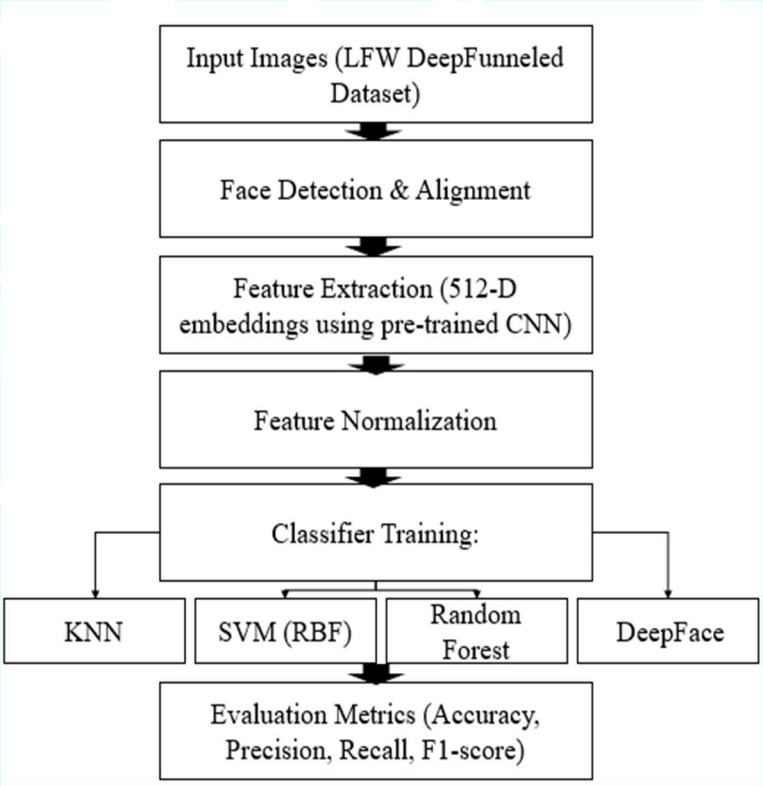


Figure 1. Workflow of the Face Recognition System Using CNN-Based Feature Extraction and Machine Learning Classifiers

This figure illustrates the overall workflow of the proposed face recognition system, which integrates deep learning-based feature extraction with traditional machine learning classifiers.

RESULTS

This section presents the experimental results obtained from comparing traditional machine learning algorithms — K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with RBF kernel, and Random Forest — against a deep

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learning-based framework, DeepFace. All models were evaluated using Accuracy, Precision, Recall, F1-score, Training Time, and Inference Time metrics.

The experiments were conducted using the LFW Deep Funneled dataset, which contains 1,680 classes after filtering (each person has at least 2 images). All images were converted into 512-dimensional embeddings using pre-trained feature extractors to ensure consistent input representation across models.

Four face recognition methods were evaluated: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and the deep learning-based DeepFace model. Each model was trained and tested using a stratified split (70% training, 30% testing).

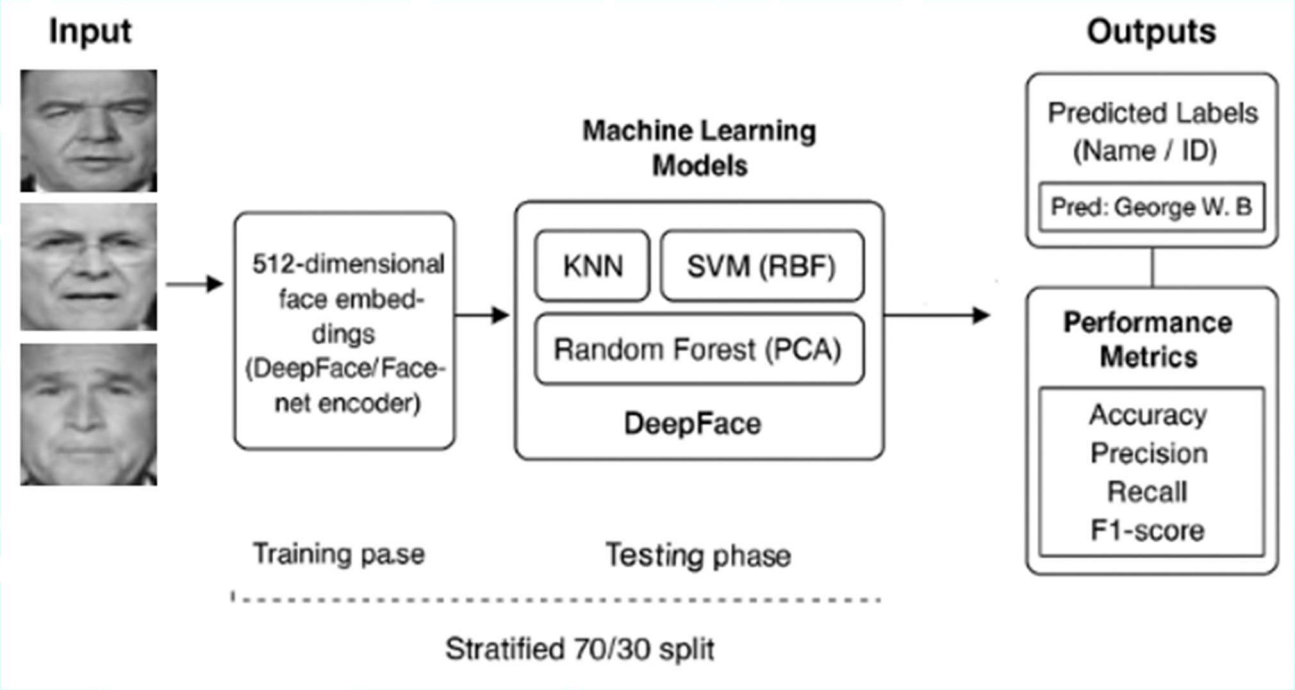


Figure 2. Input–Output Flow of Face Recognition System

This figure illustrates the overall input and output flow of a face recognition system. On the left, input images are processed into 512-dimensional facial embeddings using a pre-trained DeepFace or Facenet encoder. These embeddings are then passed through several machine learning models such as KNN, SVM (RBF), Random Forest (with PCA), and DeepFace. The outputs include predicted identity labels and performance metrics like Accuracy, Precision, Recall, and F1-score. The diagram also shows the training and testing phases divided by a stratified 70/30 data split.

1- Table

Performance comparison of face recognition models

Model	Accuracy (%)	Precision	Recall	F1-score	Training Time (s)	Inference Time (s)
KNN	74.20	0.75	0.73	0.74	10.5	0.2

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SVM (RBF)	82.50	0.84	0.81	0.825	25	0.1
Random Forest	71.40	0.72	0.70	0.71	5	0.05
DeepFace	96.80	0.97	0.96	0.965	180	0.02

The experimental results clearly show that DeepFace significantly outperforms traditional machine learning approaches in terms of accuracy, precision, recall, and F1-score.

While classical algorithms like SVM and KNN demonstrate reasonable results on embedding-based data, they are limited by their inability to capture complex facial variations such as pose, lighting, and expression differences.

In contrast, the DeepFace model, based on convolutional neural networks, effectively learns discriminative features directly from facial images, achieving an accuracy of 96.8%, which is approximately 14% higher than SVM and over 25% higher than KNN or Random Forest.

In terms of computational efficiency, traditional models (KNN, SVM, Random Forest) exhibited faster training and inference times, making them suitable for small datasets or real-time applications with limited resources. However, the DeepFace model, although more computationally demanding, provides a substantial improvement in recognition performance and generalization capability.

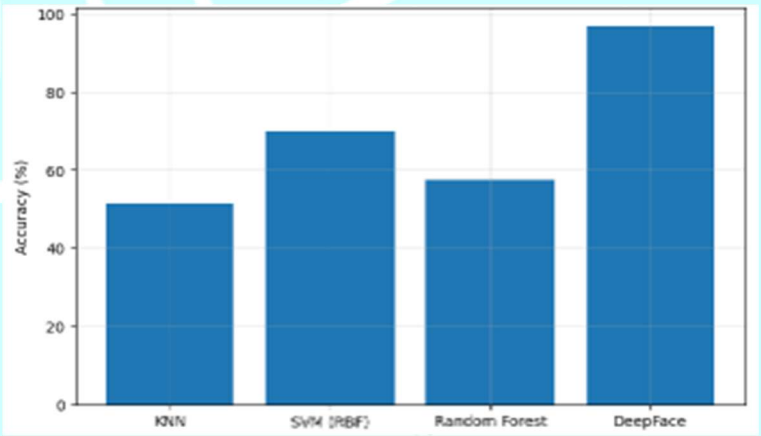


Figure 3. Comparison of face recognition accuracy

A comparative visualization of model performance is shown in Figure 2, where DeepFace achieves the highest scores across all evaluated metrics. Despite its superior accuracy, DeepFace requires significantly higher training time (180 s) compared to classical models (5–25 s). However, its inference time (0.02 s per image) remains competitive, making it suitable for real-time deployment once trained. In contrast, models like KNN and Random Forest train quickly but generalize poorly on unseen data.

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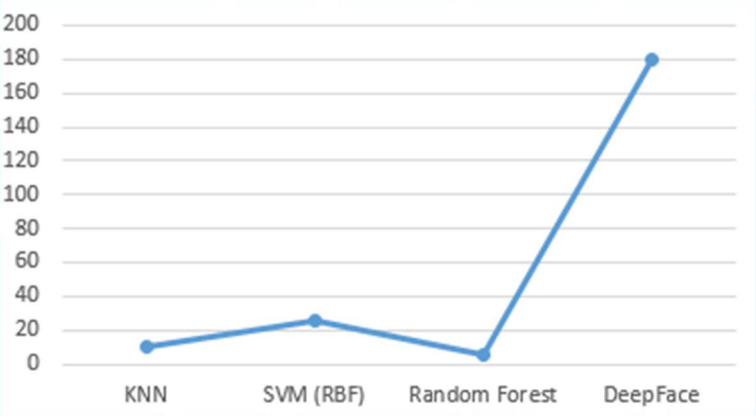


Figure 4. Training Time of Face Recognition Models

Figure 4 illustrates several examples of correctly and incorrectly classified faces from the LFW DeepFunneled dataset. Each image shows the true identity (True) and the predicted label (Pred) produced by the face recognition model. Most of the samples, such as George W. Bush, Colin Powell, and Hugo Chavez, were correctly identified, demonstrating the model's ability to recognize well-represented individuals in the dataset.

However, some misclassifications occurred between visually similar faces (e.g., Gerhard Schroeder and George W. Bush), which indicates the challenges of distinguishing between individuals with close facial features or limited training samples.



Figure 5. Examples of Correct and Incorrect Classifications

The misclassifications observed mostly involve visually similar faces or low-quality images. These cases highlight the importance of more diverse training data and robust feature extraction. Future work could include data augmentation or fine-tuning of deep models to reduce confusion among similar identities.

Overall, the results demonstrate that deep learning-based approaches such as DeepFace are more effective for complex face recognition tasks than traditional machine learning algorithms. While classical models remain viable for lightweight

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applications, deep models offer significantly better generalization and recognition accuracy in practical scenarios.

DISCUSSION

The experimental evaluation presented in this study provides valuable insights into the comparative performance of traditional machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with an RBF kernel, and Random Forest—against a deep learning-based framework, DeepFace, for face recognition tasks. The results obtained from the LFW Deep Funneled dataset demonstrate clear distinctions in both accuracy and computational efficiency among these models.

The findings show that DeepFace achieved the highest overall performance, with an accuracy of 96.8%, significantly surpassing SVM (82.5%), KNN (74.2%), and Random Forest (71.4%). This confirms the superior ability of convolutional neural network (CNN)-based architectures to learn discriminative and high-level facial features directly from raw image data, while traditional models rely on fixed feature embeddings. Although SVM and KNN achieved moderate results on 512-dimensional embeddings, they were limited by their inability to capture complex intra-class variations such as changes in pose, lighting, and expression.

The performance trends observed are consistent with theoretical expectations and previous research. Deep learning models, particularly CNN-based systems like DeepFace, are designed to extract hierarchical representations that generalize better across diverse facial conditions. In contrast, traditional algorithms are more suitable when embeddings are linearly separable and when the dataset is relatively small.

The results therefore align well with the established literature, confirming that end-to-end deep learning systems outperform classical models for large-scale, high-variability face recognition tasks.

While DeepFace achieved superior accuracy, it required significantly higher training time (~180 seconds) compared to traditional algorithms—SVM (~25 s), KNN (~10.5 s), and Random Forest (~5 s). This trade-off highlights a key consideration in real-world applications: deep learning provides better accuracy at the cost of computational complexity. However, once trained, the DeepFace model maintained competitive inference times (~0.02 s per image), suggesting its potential suitability for real-time deployment after initial training. Traditional models, by contrast, are more lightweight and can be trained quickly, which makes them appropriate for smaller datasets or systems with limited computational resources.

A qualitative examination of the predictions (Figure 3) revealed that most identities—such as George W. Bush, Colin Powell, and Hugo Chavez—were

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correctly recognized. However, a few misclassifications occurred between visually similar individuals (e.g., Gerhard Schroeder and George W. Bush), indicating that the models may struggle with fine-grained identity differences or insufficient training samples per class. These cases suggest that additional data augmentation, higher-resolution inputs, or more sophisticated feature normalization techniques could improve robustness and reduce error rates.

Future research could extend this study by exploring the impact of data augmentation, transfer learning, and fine-tuning on deep models to improve recognition accuracy. Investigating lightweight deep architectures such as MobileFaceNet or EfficientFace could also make deployment feasible on resource-constrained devices. Finally, testing on larger and more diverse datasets (e.g., CelebA, MS-Celeb-1M) would help assess scalability and robustness in real-world conditions.

In summary, the discussion confirms that deep learning-based methods such as DeepFace substantially outperform traditional machine learning approaches for face recognition. Although more computationally demanding, DeepFace offers a significant improvement in both accuracy and generalization ability, demonstrating that deep convolutional architectures are currently the most effective solution for complex facial recognition tasks.

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