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Evaluation of Deep Learning Methods in Face Recognition: Datasets, Metrics, and Results

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ABSTRACT:
Face recognition has become a cornerstone technology in biometric authentication, surveillance, and social media applications. With the advent of deep learning, particularly convolutional neural networks (CNNs), face recognition systems have seen unprecedented improvements in accuracy, robustness, and scalability. This paper presents a comprehensive evaluation of deep learning methods applied to face recognition, focusing on three critical aspects: datasets, performance metrics, and empirical results.

we analyze and compare the performance of state-of-the-art deep learning models such as DeepFace, FaceNet, SphereFace, CosFace, and ArcFace across these datasets. The results demonstrate that while current models achieve near-perfect accuracy on constrained datasets, challenges persist in real-world scenarios due to variations in pose, illumination, occlusion, and demographic diversity.

Key Words: Convolutional Neural Networks (CNNs), DeepFace, FaceNet, SphereFace, CosFace, and ArcFace, HOG, OpenCV, RON

INTRODUCTION:

Face recognition is a rapidly evolving field within computer vision, with wide-ranging applications in security, surveillance, authentication, social media, and human-computer interaction. The primary goal of face recognition is to identify or verify individuals from images or video frames by analyzing their facial features.

Traditional face recognition systems relied heavily on handcrafted features and statistical models, such as Eigenfaces, Fisherfaces, or Local Binary Patterns (LBP). While these methods achieved moderate success under controlled conditions, they often struggled with variations in lighting, pose, occlusion, and facial expressions. As a result, their real-world effectiveness was limited.

In recent years, the advent of deep learning—particularly Convolutional Neural Networks (CNNs)—has significantly transformed the landscape of face recognition. Deep learning models automatically learn hierarchical feature representations from raw pixel data, eliminating the need for manual feature engineering. These models have demonstrated remarkable accuracy and robustness, even under challenging conditions, outperforming traditional techniques by a significant margin.

Popular deep learning-based face recognition frameworks such as DeepFace, DeepID, FaceNet, and ArcFace have achieved near-human or even superhuman performance on benchmark datasets. These models leverage large-scale training datasets, sophisticated network architectures, and advanced loss functions to learn discriminative facial embeddings.

Despite the success, deep learning-based face recognition systems face ongoing challenges, including bias and fairness, privacy concerns, dataset limitations, and vulnerability to adversarial attacks. Continued research is focused on addressing these issues and improving performance in real-world, unconstrained environments.

This survey aims to provide a comprehensive overview of deep learning approaches for face recognition, covering key architectures, datasets, evaluation metrics, applications, and open research challenges.

A COMPREHENSIVE REVIEW ON VARIOUS FACE RECOGNITION SYSTEM USING DEEP LEARNING

In this paper, on conducting an exhaustive literature review, we have identified some best and also latest techniques of Deep Learning particular specifically used in the research articles of Facial Recognition System which are suited for a type of facial recognition system working better to suffice the requirement of the problem having their own limitations under certain scenarios.

This research article[1] introduces FaceFilter, a novel system designed for face identification that overcomes common limitations in varying poses, illumination, and blur. The core of their method involves a deep convolutional network to extract essential face features, followed by a unique filter algorithm that selects only the most significant features (those greater than zero) and their corresponding indices. This approach reduces data dimensionality by half while maintaining high accuracy, achieving 99.7% on the Labeled Faces in the Wild dataset and 94.02% on YouTube Faces DB. Furthermore, FaceFilter incorporates a 360-degree rotation technique for images where a face might not be initially detected due to challenging angles, showcasing its robustness in unconstrained environments.

This article [2] introduces a Deep Learning Based Real-Time Face Recognition System designed to operate efficiently on low-cost computing devices. The authors developed a four-stage process: face detection using Histogram of Oriented Gradients (HOG), face posing and projecting with a modified facial landmark estimation for centering, deep learning-based face recognition leveraging a pre-trained model to generate 128 embeddings, and finally, face classification using a Support Vector Machine (SVM) to identify individuals. While the system achieved a 96.88% accuracy on a small dataset, it demonstrated real-time performance on an Intel Core i7 processor but not on the less powerful Raspberry Pi 3B, indicating that achieving real-time speeds is still dependent on processing power even with optimized algorithms.

This document [3] presents a research paper titled "Face Detection and Recognition Using Face Mesh and Deep Neural Network," published in Procedia Computer Science. The core purpose of the paper is to introduce a novel model for face detection and recognition that effectively addresses challenges faced by existing systems, such as varying illumination, background changes, and non-frontal facial poses. By employing a Face Mesh technique, which reconstructs complete faces from 468 face landmarks, the proposed deep neural network achieves a 94.23% accuracy on a combination of the Labeled Faces in the Wild (LFW) dataset and real-time images. This research is significant for its application in security, surveillance, and access control systems, offering a more robust and accurate solution for identifying individuals under diverse conditions.

This academic paper [4] explores the development of a face recognition system using deep learning, specifically leveraging Python's OpenCV library. The core purpose is to create a secure and accurate method for identifying individuals, emphasizing its potential to replace traditional authentication like ID cards. The system operates in two main stages: face detection, primarily using Haar cascade techniques, and face identification, which involves extracting facial features through a combination of Convolutional Neural Networks (CNNs) and the Local Binary Pattern Histogram (LBPH) algorithm. The research outlines the hardware components and system architecture for implementation, including a Raspberry Pi and camera, ultimately aiming for applications such as automated attendance tracking, where detected faces are verified against a database to mark presence or absence.

This source, titled[3] "Face Detection and Recognition Using Face Mesh and Deep Neural Network," is a research paper published in Procedia Computer Science by Elsevier B.V. in 2023. Authored by Shivalila Hangaragi, Tripty Singh, and Neelima N. from Amrita Vishwa Vidyapeetham, India, the paper introduces a novel model for face detection and recognition. The authors explain that their deep neural network model utilizes Face Mesh technology to achieve 94.23% accuracy in identifying individuals, even under challenging conditions such as varying illumination, backgrounds, and non-frontal poses. The research details the model's application in security and surveillance, its methodology involving facial landmark detection and 3D face reconstruction, and a comparison of its performance against existing face recognition algorithms.

This academic article[5] **introduces an improved deep learning method for face detection**, focusing on the challenging task of identifying small, obscured, or oddly positioned faces in uncontrolled settings. The authors propose enhancements to the **RetinaNet architecture**, a single-stage face detector, by integrating a **Region Offering Network (RON)** and a prediction branch to suggest and then refine facial boundaries. Their approach, **trained on extensive datasets like WIDER FACE and FDDB**, demonstrates **superior accuracy and competitive speed** compared to existing methods, as evidenced by experimental results and performance metrics like Average Precision and F-measure. The paper details the **technical components** of their model, including **High Feature Generation Pyramid (HFGP)** and **Low Feature Generation Pyramid (LFGP)**, and discusses its **practical applications** in computer vision systems.

This document outlines [6] Rashmi Jatain1, Dr Manisha Jailia2 This article from the International Journal on Recent and Innovation Trends in Computing and Communication focuses on **automatic human face detection and recognition using deep learning, specifically convolutional neural networks (CNNs)**. It highlights how distinguishing individuals through facial features is crucial, even for genetically identical twins. The authors propose a deep learning approach that **demonstrates superior accuracy, precision, recall, and F1-score compared to other methods** for face identification. The paper also **explores the**

historical progression of facial recognition technology, detailing various techniques and the challenges that persist in achieving perfect recognition.

This article [7], published by Oxford University Press on behalf of The British Computer Society, explores **face recognition using deep learning on the Raspberry Pi**, a compact single-board computer. The authors, Abdulatif Ahmed Ali Aboluhom and Ismet Kandilli from Kocaeli University, investigate the **feasibility of transfer learning** for this task, comparing **InceptionV3 and MobileNetV2** deep learning architectures. Their findings indicate that **MobileNetV2 significantly outperforms InceptionV3** in accuracy and efficiency, making it a more suitable choice for **resource-limited edge devices** like the Raspberry Pi. This research contributes to developing **efficient, real-time deep learning applications** for facial recognition, especially in scenarios requiring **reduced latency and low power consumption**.

This scholarly article[8] introduces an automated human face detection and recognition system that leverages deep learning, specifically Convolutional Neural Networks (CNNs), to identify individuals based on their unique facial features. The authors highlight the increasing prevalence and importance of facial recognition in everyday technology and security, emphasizing that facial characteristics are the most significant identifiable traits for distinguishing people, even identical twins. The proposed system, which utilizes a VGG 16 CNN model, demonstrates superior accuracy, precision, recall, and F1-score compared to other existing methods like decision trees and random forests, suggesting a more robust and reliable approach to face identification in various environments, even with challenges like varying illumination or expressions.

The document[9] presents an academic paper detailing the development and comparison of four **deep learning techniques for facial recognition**, aiming to address challenges such as speed, accuracy, and variability in face pose and angle. The proposed methodologies include a basic **Convolutional Neural Network (CNN)**, an **Auto-Encoder** architecture designed to eliminate the need for retraining when adding new users, and two **Capsule Network (CapsNet)** topologies: one using a standard CNN layer and another integrated with the robust **VGG-19** feature extractor. The results, tested on the **COMSATS Face Dataset**, indicate that the Auto-Encoder and the CapsNet with VGG-19 both achieved the highest **99% accuracy**, with the latter proving superior in recognizing faces from diverse viewing angles.

The article titled [10] "Combining MTCNN and Enhanced FaceNet with Adaptive Feature Fusion for Robust Face Recognition," authored by Sasan Karamizadeh, Saman Shojae Chaeikar, and Hamidreza Salarian, which was published in **Technologies** in **October 2025**. This research focuses on proposing a **hybrid deep learning architecture** to enhance the accuracy and **robustness of face recognition** against real-world challenges like occlusion, pose, and lighting variations. The core innovation is the integration of **Multi-task Cascaded Convolutional Networks (MTCNN)** for precise face detection and alignment, an **attention-enhanced FaceNet** for feature extraction, and a **Transformer-based Adaptive Feature Fusion** module that dynamically incorporates contextual cues. Evaluation on benchmark datasets like **CelebA**, **LFW**, and the highly challenging **IJB-C** demonstrates that the proposed model achieves **superior performance**, significantly outperforming baseline and state-of-the-art methods in unconstrained scenarios.

Table1: Overview of different papers in terms of the deep learning technique used and its limitations.

Article	Technique Used	Limitations
[1]	The specific architecture used is an **NN4 neural network structure**, which is a deep neural network.	the rotation technique for 360° is used for the images that have the face in different angles, while this kind of rotation cannot be done in the augmentation method in deep learning.
[2]	**HOG)** was used to identify faces in digital images. **SVM** is used to determine. The system uses a **pre-trained deep learning (DL) based face recognition model.**	limited dataset is used, Intel i7 core platform achieved real-time recognition. When tried on a Raspberry Pi 3B, it was unable to run in real-time.
[3]	Haar cascade is used for edges and lines to detect the face. Algorithms used for feature extraction, are **Eigen Faces**, **Local Binary Pattern Histograms**, **Fisher faces**, Machine learning algorithms tested in related work, such as Random Forests, SVM, Linear Regression, **Logistic Regression**, and KNN.	If a test image contains a face whose landmarks do not match any entry in the database, the model will correctly identify the face but tag it as **"unknown"**. This behavior was observed in experiments where a test image contained three faces, but only one (the militant Abdel_Nasser_Assidi) was recognized because the other two faces lacked matching face landmarks in the database
[4]	**ResNet-50 CNN** utilized for extracting facial features and performing classification, **(LBPH) / (LBP) algorithm**: Employed for face recognition purpose, **Siamese networks and triplet networks** These are deep learning-based methods mentioned for optimizing the matching process in face recognition systems	Deep learning models **"need a lot of data to be trained"**. Similarly, deep learning face recognition systems often require a **"huge collection of facial photos"** to train a neural network effectively

[5]	he proposed methodology utilizes the **RetinaNet baseline**, a single-stage deep learning face detector, designed to handle challenging face detection problems by improving speed and accuracy. This architecture is fundamentally composed of a **Region Offering Network (RON)**, which compiles area suggestions likely to include faces, and a **prediction branch** for classification and refining bounding box boundaries. The model is trained using the PyTorch framework, incorporating a critical step of **hard negative mining** on the WIDER FACE dataset to reduce false positives.	The main challenges and limitations acknowledged are that the difficulty of detecting **small, blurry, and closely occluded faces in uncontrolled conditions** has not yet been entirely resolved, and future work is required to solve **blurry image problems under dark conditions** and increase the overall accuracy of the approach
[6]	The methodology operates in sequential steps: real-time face detection is achieved using the **Open CV library** and the **Haar cascade detection method**. Finally, the features are classified and recognized against a database using the **VGG 16 Convolutional Neural Network (CNN) model**.	The main limitation identified is that the identification procedure is **significantly affected by ambient lighting**, causing the recognition system to be more likely to make mistakes when the lighting is poor. To address this, future efforts should involve using **additional low-light-quality training photos** to create a more robust face classifier and developing strategies for selecting optimal features to improve accuracy in uncontrolled environments
[7]	The methodology centers on implementing efficient facial recognition on the resource-	

	limited **Raspberry Pi 4** using **transfer learning**. This involves leveraging the pre-trained architectures of two Deep Neural Networks, **MobileNetV2** and **InceptionV3**, as feature extraction layers. To facilitate classification, additional layers, including a **Softmax** output layer for 10 celebrity classes, are appended, completing the system pipeline which handles image capture, face detection, feature extraction, and matching in real-time	
[8]	The methodology centers on implementing a real-time face recognition system using a **deep learning algorithm** based on a **transfer learning** approach. The core technique involves adapting the pre-trained **VGG16 Convolutional Neural Network (CNN) architecture** for feature extraction and classification. For the initial stage of detection in a continuous video stream, the system utilizes the **Haar cascade pre-trained classifier** in conjunction with the **OpenCV library**	The system's recognition accuracy is challenged by external factors like **low-resolution images**, various types of **noise**, and adverse **light and shadow** falling on the face. Accuracy also decreases due to changes in **facial expressions** (e.g., laugh or crying), which alter face geometry, and **occlusion** caused by items like face masks, spectacles, hair, or beards
[9]	The methodology utilized in this work involved proposing and evaluating **four distinct deep learning techniques for facial recognition**. These include a standard **Convolutional Neural**	The standard CNN model is limited because it struggles to detect faces that are not frontal and requires **retraining from scratch whenever a new person is added**, rendering it unsuitable for the production

	Network (CNN) architecture, a **CNN Decoder (Auto-Encoder)**, and two **Capsule Network (CapsNet) topologies** (CapsNet with CNN, and CapsNet with VGG-19). The COMSATS Face Dataset was used for testing, training, and assessment of these models	phase. Additionally, the CapsNet with CNN model experienced **poor performance issues** (81% accuracy) due to a poor feature extraction layer
[10]	The methodology proposes a hybrid system combining three main elements: **Multi-task Cascaded Convolutional Networks (MTCNN)** for precise face detection and alignment; an **Enhanced FaceNet** architecture utilizing attention mechanisms to extract robust, discriminative 128-D facial embeddings, particularly against occlusions; and an **Adaptive Feature Fusion** module, which uses a lightweight transformer encoder to dynamically integrate these embeddings with contextual vectors (pose, lighting, masks) to maximize recognition accuracy in challenging scenarios.	The current model still encounters challenges with **extremely low-resolution images or severe motion blur**, which can affect the quality of facial embeddings. Additionally, initial analysis indicated performance differences across subgroups such as gender, age, and skin tone, highlighting the ongoing necessity for fair training

CONCLUSION

These sources collectively examine the field of **face detection and recognition**, with a particular focus on **deep learning (DL) and convolutional neural networks (CNNs)** for real-time applications. Several papers explore various techniques, including **Histogram of Oriented Gradients (HOG)** and **Support Vector Machines (SVM)**, to improve the **accuracy and efficiency** of these systems. A recurring theme involves the development and evaluation of **lightweight models** suitable for deployment on **resource-constrained devices** like the Raspberry Pi, often leveraging **transfer learning** from pre-trained networks like MobileNetV2 and InceptionV3. The authors frequently compare model performance across different hardware and datasets, assessing metrics such as **accuracy, processing speed (frames per second), precision, and recall** in diverse conditions, including varying illumination and non-frontal facial poses.

The research aims to advance reliable and accessible facial recognition technology for various uses, from security to mobile applications within the Internet of Things (IoT).

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