International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Literature Survey on Face Recognition with Hybrid Deep Learning

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Submitted:12/03/2024 **Revised:** 27/04/2024 **Accepted:** 04/05/2024

Abstract: These Face recognition has made remarkable progress with the advent of deep learning techniques. However, accuracy and robustness are still critical for real-world applications. This survey paper explores the synergy between traditional and deep learning methods, providing a comprehensive analysis of hybrid deep learning models for face recognition. We first discuss the foundational techniques in traditional face recognition, such as eigenfaces, local binary patterns (LBP), and histogram of oriented gradients (HOG). These methods laid the groundwork for subsequent developments. We then introduce convolutional neural networks (CNNs), Siamese networks, and FaceNet, which are deep learning models that automate feature extraction from raw facial data.We also discuss the advantages and disadvantages of traditional and deep learning methods, as well as the challenges of hybrid deep learning models. Finally, we present an overview of the state-of-the-art hybrid deep learning models for face recognition. Focus of this survey is the concept of hybridization, where traditional and deep features harmoniously coexist. We provide a detailed examination of key hybrid models, such as DeepID, VGG-Face, and SphereFace, elucidating their architectures, components, and contributions to the field. Additionally, we delve into the integration of face detection and alignment techniques within hybrid models, underlining their significance in achieving accurate and standardized recognition. This paper also presents the latest literature on the Hybrid face recognition models and the techniques used. The paper highlights the advantages of hybrid models, including enhanced robustness, improved accuracy, and computational efficiency, while acknowledging challenges such as data requirements, computational resources, and ethical considerations. It concludes by underscoring the promising future of hybrid deep learning models in elevating the performance and responsible deployment of face recognition systems across various domains, from security and surveillance to human-computer interaction. This survey not only encapsulates the state-of-the-art but also beckons researchers and practitioners to delve deeper into the evolving landscape of face recognition with hybrid deep learning models.

Keywords: *Face Recognition ,Hybrid Deep Learning, local binary patterns.*

1. Introduction

Face recognition, a pivotal subfield within computer vision and biometrics, has garnered significant attention due to its wide-ranging applications in security, surveillance, authentication, and human-computer interaction. The fundamental premise of face recognition is the automated identification and verification of individuals based on their facial characteristics, making it a critical component in various domains where identity verification is paramount. In this exploration of face recognition's evolution and significance, we commence with an overview of its historical context, shedding light on the foundational techniques that have shaped the landscape of this field and continue to influence the development of hybrid deep learning models.

1.A. Background and Context of Face Recognition

Face recognition is a key subfield of computer vision and biometrics that has attracted a lot of attention due to its wide range of applications in security, surveillance, authentication, and human-computer interaction. The basic concept of face recognition is the automated identification and verification of people based on their facial features, making it a critical component in various areas where identity verification is essential.

1.A.1 Historical Evolution:

The history of face recognition research dates back to the 1960s, when early attempts were made using simple geometric features. Over the years, the field has made significant progress, moving from traditional methods to the modern era of deep learning. Early methods, such as eigenfaces and Fisherfaces, helped to lay the foundation for understanding facial feature extraction and dimensionality reduction. However, these techniques had inherent limitations in handling variations in lighting, pose, facial expression, and occlusion. Deep learning methods, such as convolutional neural networks (CNNs), have overcome these limitations and achieved state-of-the-art performance in face recognition. CNNs can learn robust features from raw facial data, even in the presence of challenges such as variations in lighting, pose, and facial expression.As a result of these advances, face recognition is used in a wide range of applications, such as security, surveillance, and authentication.

1.A.2 Significance and Relevance

Face recognition is a powerful technology that can be used to authenticate people's identities in a seamless and secure way. It has a wide range of applications, from unlocking smartphones to ensuring the safety of public spaces. Face recognition systems first initiates extracting unique features from a person's face and comparing them to a database of known faces. If the features match, the system can be used to authenticate the person's identity. Face recognition systems are becoming increasingly common in our daily lives. They are used in smartphones, laptops, and other devices to unlock them. They are also used in security systems to control access to buildings and other restricted areas. In addition, face recognition systems are being used in law enforcement to identify criminals and missing persons. Face recognition systems have the potential to make our lives more convenient and secure. However, it is important to note that they are not without their challenges. For example, face recognition systems can be fooled by masks or other disguises. Additionally, they can be biased against certain groups of people. Despite these challenges, face recognition is a promising technology with the potential to revolutionize the way we authenticate people's identities.

1.A.3 Challenges in Face Recognition

While the promise of face recognition is immense, it is not without its challenges. Variability in real-world scenarios, including changes in illumination, pose, expressions, and the presence of accessories or facial hair, poses formidable hurdles to accurate recognition. Additionally, concerns related to privacy, bias, and ethical implications have sparked important discussions within the research community.

1.A.4 The Advent of Deep Learning

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs)[8], has revolutionized face recognition. Deep learning models have demonstrated remarkable abilities in automatically extracting discriminative features from raw image data, paving the way for a new era in the field. However, pure deep learning approaches are not always sufficient to address the inherent challenges of face recognition comprehensively. Given the multifaceted nature of face recognition and the complexities inherent in real-world scenarios, hybrid deep learning models have emerged as a promising solution. These models integrate the strengths of traditional techniques with the representational power of deep learning, offering improved accuracy, robustness, and adaptability. In the following sections, we delve into the nuances of hybrid deep learning models in face recognition, discussing their methodologies, applications, and the evolving landscape of this dynamic field.

Significance and relevance of hybrid deep learning models

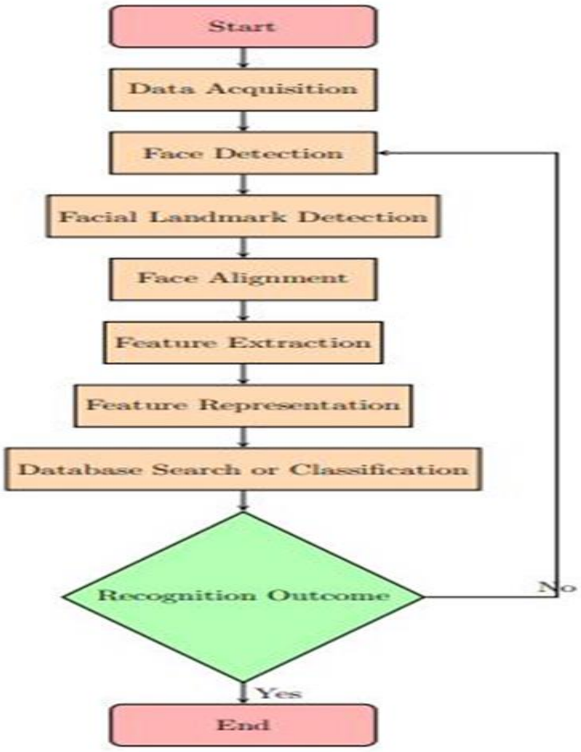
Hybrid deep learning models for face recognition are important in computer vision and biometrics. They are a bridge between traditional and cutting-edge methods, and can effectively tackle the challenges of real-world face data. By combining the insights of traditional techniques with the power of deep learning, hybrid models can improve the accuracy and robustness of face recognition systems. They are relevant to many practical applications, such as securing digital devices and improving surveillance and access control.

Research Objective:

This research aims to critically examine and compare traditional face recognition algorithms that use manually designed features, such as Eigenfaces, Fisherfaces, ICA-based SVM, LBP-based methods, and their variants, with contemporary deep learning-based approaches. We will elucidate the strengths, weaknesses, and performance characteristics of these traditional algorithms in comparison to deep convolutional neural networks (CNNs). By conducting a comprehensive review and comparative analysis, we hope to provide insights into the evolution of face recognition techniques and highlight the key advancements that have led the field from non-deep learning methods to the deep learning era, with a focus on the pivotal role played by hybrid models in bridging these paradigms. This research objective is consistent with the historical context provided, which introduces conventional face recognition methods and discusses the transition to deep learning approaches. The objective emphasizes the need to critically evaluate and compare these two paradigms, which is a common focus in the literature on face recognition.

Traditional Face Recognition Techniques: In this section, traditional face recognition process is presented and some Face Recognition techniques are discussed. The face recognition process begins with data acquisition, where facial images or videos are captured using cameras or imaging devices. These acquired data are then subjected to face detection algorithms, which identify and locate potential faces. Facial landmark detection may follow, pinpointing key facial features. Next, facial alignment techniques are employed to standardize the position and orientation of detected faces. Traditional feature extraction methods capture specific facial characteristics, while deep feature extraction using Convolutional Neural Networks (CNNs) learns abstract features from raw images. Extracted features are then represented and processed for database search or classification, leading to the recognition outcome. The process iterates until recognition success (Yes) or further face detection is required (No), maintaining a seamless flow in the face recognition pipeline.

The flow of face recognition:



Face Recognition process.

Overview of Traditional Techniques:

Traditional face recognition techniques, which predominate prior to the deep learning revolution, were characterized by their reliance on handcrafted features and classical machine learning algorithms. Among the notable traditional methods, Eigenfaces, Local Binary Patterns (LBP), and Histogram of Oriented Gradients (HOG) are prominent examples.

Eigenfaces: Eigenfaces, introduced as one of the pioneering methods in the field, reshaped grayscale face images into one-dimensional vectors, effectively reducing the dimensionality of the data. Principal Component Analysis (PCA) was then applied to derive a low-dimensional subspace where the feature distributions of similar faces were compacted. This subspace served as a representation for all face samples. For face recognition, Eigenface computed the Euclidean distance between a query face image's feature vector and those of known gallery face features within the subspace. The category of the query image was predicted based on the smallest distance to gallery features.

LBP and HOG: Other traditional techniques like Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) focused on different feature extraction strategies. Chen[31] has detailed about this LPB and HOG approach. LBP characterized facial texture by examining local pixel patterns, while HOG analyzed the distribution of gradient orientations. These methods aimed to capture distinctive patterns and structures in facial images, providing valuable cues for recognition.

Strengths and Limitations of Traditional Methods: Traditional face recognition methods had their merits. They were computationally efficient and interpretable, enabling practitioners to understand the reasoning behind recognition decisions. Additionally, these techniques often performed well under controlled conditions and with minimal computational resources.

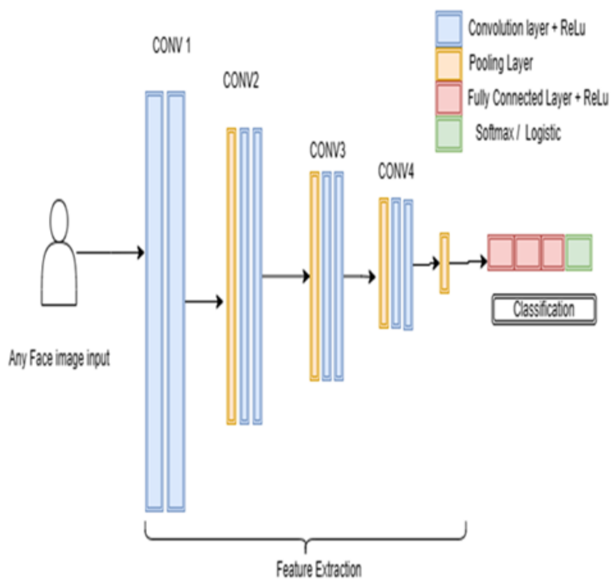
However, their limitations became evident when applied to real-world scenarios. Traditional methods struggled with variations in lighting conditions, pose changes, facial expressions, and occlusions. The reliance on handcrafted features limited their ability to adapt to diverse and complex facial data. Foundation for Hybrid Approaches.Despite their shortcomings, traditional techniques played a pivotal role in laying the foundation for hybrid approaches. They demonstrated the importance of feature extraction and dimensionality reduction, which remain integral components of contemporary face recognition systems. Benradi [6] explained the significance of Hybrid approaches. By understanding the strengths and weaknesses of these traditional methods, researchers were better equipped to devise hybrid models that combine their strengths with the representational power of deep learning, as we explore in Section 2.

Deep Learning in Face Recognition

Introduction to Deep Learning and Its Application in Face Recognition: Deep learning is a part of machine learning that has been really successful in different areas, like computer vision. When it comes to recognizing faces, deep learning is a big change from how we used to do things with traditional methods. There are several works on deep learning for face recognition such as Thanh Thi Nguyen et Al [3], Banumalar et Al[4], S.Hangaragi et Al[5], Guodong et Al[15], At its core, deep learning leverages artificial neural networks with multiple layers, enabling the automatic extraction and representation of intricate features directly from raw image data. This capability is particularly well-suited for face recognition because facial images contain a wealth of subtle details and patterns that are challenging to capture using manual feature engineering.In the world of recognizing faces, deep learning models, especially Convolutional Neural Networks (CNNs), have become the most important part of modern methods. CNNs are designed to mimic the visual processing of the human brain, employing layers of convolutional and pooling operations to hierarchically extract features from an input image. The deep architecture of CNNs allows them to learn increasingly abstract and discriminative features as information flows through successive layers. These learned features are critical for distinguishing between different individuals based on their facial characteristics.

Overview of Deep Learning Models (e.g., CNNs, Siamese Networks, FaceNet):

Convolutional Neural Networks (CNNs): CNNs have become the workhorse of deep learning-based face recognition. Wang et Al[18], Aneesa et Al[17] has presented a survey on face recognition using CNNs. These networks consist of convolutional layers that learn spatial hierarchies of features, enabling them to



CNN based Face Recognition Process

capture both low-level details (such as edges and textures) and high-level abstractions (such as facial expressions and identities). CNNs are typically used for face classification and feature extraction.The following figure explains the CNN based Face recognition.

Siamese Networks:

Siamese networks are a special kind of neural network made for checking if two faces are the same or not. They consist of two identical subnetworks, each of which takes an input image as input. The two subnetworks share the same weights, which means that they learn to extract the same features from the input images. This allows the Siamese network to compare the similarity or dissimilarity between two faces by comparing the features extracted from the two images. This makes Siamese networks suitable for one-shot or few-shot face recognition scenarios, where only a few examples of each face are available for training.

C. Song et al. [19] and Chatterjee et al. [20] have presented face recognition methods using Siamese networks. Their methods have achieved state-of-the-art results on several benchmark face recognition datasets.

FaceNet: FaceNet is a complex computer program for recognizing faces made by Google. It employs a special kind of neural network called a deep convolutional neural network (CNN). This network turns pictures of faces into a bunch of numbers, and the distance between these numbers tells us how similar the faces are. This innovative approach has significantly advanced the accuracy of face recognition and played a pivotal role in the deep learning revolution in this field.A detailed approach is presented by Xu et Al[21]. FaceNet's innovative approach has significantly advanced the accuracy of face recognition and played a pivotal role in the deep learning revolution in this field.

Deep Learning for Face Recognition: Capabilities and Challenges:

Deep learning has brought remarkable capabilities to face recognition. Its ability to automatically learn discriminative features from raw data has led to substantial improvements in accuracy, even in the presence of challenging factors such as variations in lighting, pose, facial expressions, and occlusions [22]. Deep learning models can generalize well to unseen faces, making them suitable for a wide range of applications. However, there are challenges still with the Deep learning based Face Recognition. The challenges begins with labellling large datasets, which is a costly operation interms of labor, acquisition. Agreed to that, deep learning models are computationally intensive, requiring heavy processing power and huge memory.

This limits the deployment capability in real time applications[23]. Additionally, the ethical and practical deployment of face recognition systems hinges on the interpretability of deep learning models and concerns surrounding bias and fairness. To conclude this section, deep learning has revolutionized face recognition by enabling automatic feature extraction and representation. CNNs, Siamese Networks, and models like FaceNet have significantly improved accuracy. However, data requirements, computational demands, and ethical considerations remain essential factors to address in the advancement and deployment of deep learning-based face recognition systems.

3. Need for Hybrid Deep Learning

Deep learning has attained state-of-the-art performance in face recognition, but it does come with inherent limitations[8]. Major limitation is the computational expense associated with training and deploying deep learning models. Moreover, these models can be susceptible to noise and variations in lighting and pose. Another drawback of deep learning is its challenge in interpreting the learned features. This can create difficulties in debugging the model and comprehending the rationale behind its specific predictions. In response to these constraints, researchers have initiated investigations into hybrid deep learning models, amalgamating conventional methods with deep learning. Conventional techniques like Gabor filters and PCA can be applied to extract features resilient to noise and lighting or pose variations. Subsequently, these features can serve as the foundation for training a deep learning model, surpassing the performance of a purely deep learning approach. Beyond performance enhancement, hybrid deep learning models may also offer improved interpretability compared to their pure deep learning counterparts. This stems from the ability of traditional techniques to elucidate the features acquired by the deep learning model.

Motivation for Combining Traditional Techniques with Deep Learning

There exists essential reasons to combine traditional techniques with deep learning for face recognition.

Some of the reasons are listed below.

1. Enhanced Resistance to Noise and Variations: Traditional methods, such as Gabor filters and PCA, frequently exhibit greater resistance to noise and variations in lighting and pose compared to deep learning models due to their feature extraction design.

2. Enhanced Explanatory Capability: Traditional techniques enable the elucidation of features acquired by the deep learning model, facilitating model debugging and comprehension of prediction rationale.

3. Performance Enhancement: Hybrid deep learning models have demonstrated superior performance in face recognition when contrasted with pure deep learning models, primarily due to the traditional techniques' ability to enhance model robustness and interpretability. In summary, hybrid deep learning shows promise in face recognition by combining traditional strengths with deep learning's power, leading to improved performance, robustness, and interpretability. Furthermore, aside from the mentioned advantages, there are other potential benefits to using hybrid deep learning in face recognition. For instance, hybrid models might be easier and more adaptable for training and deployment than pure deep learning models. While research on hybrid deep learning for face recognition is still in its infancy, early results are encouraging. Hybrid models have the potential to transform face recognition, making it more dependable, efficient, and accessible.

4. Hybrid Deep Learning Approaches

Concept of Hybrid Deep Learning Models:

Hybrid face recognition models merge the strengths of traditional methods with the advanced capabilities of deep learning. They tackle the challenges in face recognition, such as lighting, poses, expressions, and occlusions, by harnessing the complementary aspects of both traditional and deep learning approaches. Hybrid models excel in combining feature extraction and representation techniques from traditional methods with deep neural networks' feature learning prowess. Traditional methods like Eigenfaces, LBP, and HOG have proven effective at capturing specific facial attributes. They offer interpretability and computational efficiency but may struggle with real-world data complexities. In contrast, deep learning excels at autonomously learning intricate, distinctive features directly from raw images, making it adept at handling intricate facial data variations. By uniting these two paradigms, hybrid models aim to bolster the resilience and precision of face recognition systems.

Overview of Feature Extraction and Representation Techniques:

Hybrid deep learning models integrate a diverse set of feature extraction and representation techniques from traditional methods. For example, Eigenfaces break down facial images into eigenvalues and eigenvectors, offering insights into facial shape variations and capturing the global facial structure. Local Binary Patterns (LBP) excel at encoding texture information by analyzing pixel intensity patterns in local image regions. Histogram of Oriented Gradients (HOG) concentrates on gradient orientations, describing edge direction distribution across the face. In hybrid models, these traditional features serve as foundational elements, offering interpretable and informative representations of specific facial characteristics like shape, texture, and local structures. Combined with deep learning's capacity to capture high-level abstract features, they create a comprehensive and distinctive feature space that enhances the face recognition process.

Fusion Strategies for Combining Traditional and Deep Features:

The integration of traditional and deep features is a crucial element in hybrid deep learning models. Various fusion strategies have been investigated to efficiently merge these features:

Early Fusion: In early fusion, traditional features are integrated with deep features at the network's initial stages, often as supplementary input channels. This enables the model to concurrently learn from both feature sets, allowing the network to adapt to their distinct attributes.

Late Fusion: Late fusion takes place after feature extraction from both traditional and deep learning branches. The features are either concatenated or combined using methods like weighted averaging or distance-based fusion during the final decision-making phase.

Intermediate Fusion: Intermediate fusion involves the fusion of representations from traditional and deep learning pathways at intermediary network layers. This method supports joint feature learning and can bolster the model's capacity to capture pertinent information.

Ensemble Methods: Hybrid models can also utilize ensemble strategies like stacking or boosting to amalgamate the forecasts of traditional and deep models. This ensemble approach frequently results in enhanced accuracy and resilience.

Hybrid deep learning models, combining traditional and deep features, provide a versatile and robust approach to tackle face recognition challenges. These models excel at capturing intricate facial details while also delivering the interpretability and efficiency essential for real-world applications. They showcase the harmonious blend of classical computer vision methods with the revolutionary potential of deep learning, offering a promising path for the advancement of face recognition

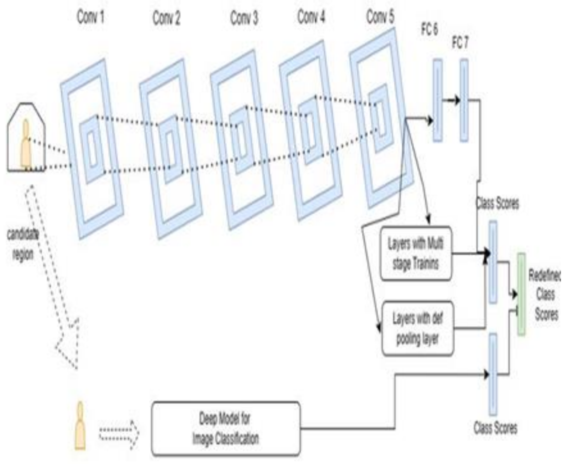
5. Key Hybrid Deep Learning Models

A comprehensive exploration of prominent hybrid deep learning models, such as DeepID, VGG-Face, and SphereFace, reveals their pivotal roles in enhancing face recognition accuracy and robustness. These models have collectively propelled the field forward with their noteworthy contributions.

DeepID:

DeepID[26] is a leading hybrid deep learning model developed by researchers from Chinese University of Hong Kong. It introduced the concept of combining traditional metric learning with deep neural networks. DeepID employs two primary components: one for traditional feature extraction and metric learning, and another for deep learning-based feature representation. The model optimizes the fusion of these two components during training to improve recognition accuracy. DeepID comprises two sibling networks.

The initial network uses older methods like Gabor filters and Histograms of Oriented Gradients (HOG) to analyze a face picture and find specific characteristics. The second network uses advanced deep learning to find complex features in the same image. These two networks are linked together through a weighted fusion layer that blends the older and deep features in the best possible way.The entire model is trained end-to-end, allowing it to learn to adaptively use both types of features for improved face recognition. The DeepID working flow is mentioned in figure 3.



DeepID working flow

VGG-Face:

VGG-Face[27], an extension of the renowned VGGNet architecture, focuses on feature extraction from face images. This hybrid model combines the VGGNet's deep convolutional layers with traditional techniques like PCA for dimensionality reduction. By exploiting both fine-grained deep features and high-level abstract representations, VGG-Face achieves state-of-the-art accuracy in face recognition tasks. VGG-Face adopts the architecture of the VGGNet, which consists of multiple convolutional and pooling layers. The model leverages the deep layers of VGGNet to capture hierarchical features from face images. Following deep feature extraction, VGG-Face employs Principal Component Analysis (PCA) to diminish dimensionality and acquire condensed representations. The ultimate classification is executed through a classifier like Softmax. The amalgamation of deep features with dimensionality-reduced traditional features augments recognition accuracy.

SphereFace:

SphereFace[28] adopts a distinctive approach by incorporating the notion of a hypersphere manifold. Its objective is to acquire discriminative features by compelling the network to map similar faces closer on the surface of the hypersphere. SphereFace combines the capabilities of deep neural networks with traditional metric learning constraints, ensuring that the learned representations are both concise and distinguishing. SphereFace introduces the concept of the angular margin loss function, which encourages the network to map faces to specific points on a hypersphere. The architecture of SphereFace relies on deep convolutional layers that acquire discriminative features. The network is complemented by the angular margin loss layer, which enforces compactness within classes and separation between classes within the hypersphere space. SphereFace's architecture underscores the significance of both deep feature learning and metric learning constraints.

Contributions to the Field:

These hybrid models have significantly advanced the domain of face recognition by closing the divide between traditional and deep learning methods. They have showcased that through the thoughtful integration of traditional and deep features, it's feasible to attain unparalleled accuracy and resilience in face recognition assignments. Furthermore, these models have offered valuable perspectives on the collaboration between manually crafted features and autonomously acquired deep representations, thereby enhancing our comprehension of effective hybrid methods in computer vision.

5. 1 Latest Hybrid Face Recognition models.

Benradi[6] introduced a novel approach to improving facial recognition accuracy in the presence of variations and occlusion. Their method integrates feature extraction techniques including Histogram of Oriented Gradient (HOG), Scale Invariant Feature Transform (SIFT), Gabor filters, and the Canny contour detector with a Convolutional Neural Network (CNN) architecture. Through experiments utilizing data from the ORL and Sheffield faces databases, Benradi achieved notable results, with the SIFT+CNN combination attaining accuracy rates of up to 100%.

Shahina et Al[2] introduces a novel Hybrid Ensemble Convolutional Neural Network (HE-CNN) framework for enhancing face recognition systems, encompassing face detection, alignment, and recognition. Despite challenges posed by unconstrained factors like pose variation, illumination, aging, occlusion, and low resolution, traditional face recognition methods exhibit limitations in such environments. Deep learning architectures have increasingly addressed these challenges, yet the pursuit of a resilient system persists. The proposed HE-CNN framework leverages ensemble transfer learning from modified pre-trained models, incorporating progressive training to significantly improve recognition accuracy. Through modifications in classification layers and the training process, Shahina et Al[2]'s framework achieves state-of-the-art results, demonstrating robustness and efficacy. Rigorous evaluation using a self-created criminal dataset showcases real-time facial recognition capabilities, with accuracies reaching 99.35%, 91.58%, and 95% on labeled faces in the wild (LFW), cross-pose LFW, and self-created datasets, respectively.

Zhenfeng et al[32] . introduce RFR-DLVT, a hybrid method that combines Deep Learning (DL) and visual tracking for effective face recognition (FR). The approach involves segmenting video sequences into reference frames (RFs) and non-reference frames (NRFs), followed by DL-based FR on RFs and Kernelized-correlation-filters-based visual tracking on NRFs to expedite FR. Experimental evaluation on standard datasets showcases superior performance, with RFR-DLVT achieving an impressive 99.6% accuracy and operating at an efficient 30 frames per second (FPS) in real-time FR on real-life surveillance videos.

Vijaya et al [1] presents a novel hybrid biometric software application tailored for facial recognition amidst challenging environmental conditions. Human face recognition, a prominent area in biometric research, encounters numerous challenges including variations in camera type, pose, lighting conditions, resolution, eyewear, and facial expressions. The proposed system integrates two key features: Laplace of Gaussian filter-based Discrete Wavelet Transform (LGDWT) and Discrete Cosine Transform Compressed-based Log Gabor Filter (DCTLGF). These features are then employed by a Multiclass Support Vector Machine (MSVM) classifier to establish the individual class labels of faces. The efficacy of the system was evaluated on a dataset comprising 200 face images from 25 individuals, captured using a five-megapixel low-resolution web camera. The results demonstrate significant improvements over existing techniques across various experimental scenarios.

Sajjad et al [7] delves into the multifaceted realm of Facial Expression Recognition (FER), an evolving research domain with applications spanning healthcare, security, and intelligent driving systems. FER, mimicking human facial expression decoding, enriches communication by complementing verbal cues. Recent advancements leverage deep learning and artificial intelligence (AI) techniques, incorporating edge modules for real-time efficiency. However, existing FER surveys primarily focus on hand-crafted techniques, overlooking edge vision-inspired deep learning and AI-based FER technologies. Sajjad's study meticulously examines the literature on FER, elucidating methodological workflows, intrinsic steps, and pattern structures. By scrutinizing FER datasets, associated challenges, and evaluation metrics, the study broadens its scope to encompass edge vision applications, such as smartphone or Raspberry Pi devices. Sajjad concludes by outlining recommendations and future research directions to advance FER technologies further.

Ram Krishn Mishra et al [14] explores the significance of image processing, a technique pivotal for enhancing images and extracting pertinent information across various domains including robotics, vision, pattern recognition, video processing, and medicine. Specifically, facial recognition stands out as a notable application within image processing, particularly in discerning human expressions. Mishra's research focuses on assessing the efficacy of deep learning and transfer learning methods such as CNN, LSTM, Inception, ResNet, VGG, Xception, and InceptionResnet in categorizing human facial expressions, notably happiness and anger. The proposed Deep Hybrid Learning (DHL) approach integrates transfer learning and deep neural networks to classify facial expressions, aiming to improve prediction and classification accuracy by amalgamating multiple deep learning models. The proposed model achieves a testing accuracy of 81.42% and a training accuracy of 95.93% utilizing a multisource image dataset.

Bui [10] examines the pivotal role of face recognition, a biometric system crucial for identifying individuals from digital images, particularly employed in security and monitoring contexts. The recent surge in research on deep neural networks for facial recognition has yielded promising results. In this study, Bui proposes a robust model designed to address face recognition challenges, particularly suitable for real-time camera applications. The study delineates two key phases: face detection and face identification. The face detection method integrates HOG features and SVM linear classifier, while the face recognition model is founded on CNN—convolution neural network principles. Through evaluation on datasets including FEI, LFW, and UOF, the proposed model demonstrates high accuracy, underscoring its efficacy in practical face recognition scenarios.

Kortli's et al[11], offers a detailed overview of face recognition techniques, emphasizing local, holistic, and hybrid approaches. The paper meticulously assesses the current state-of-the-art in face recognition methods, delineating their strengths and limitations across various contexts. It also highlights prevalent face databases used for testing these techniques and identifies emerging research avenues. Korlil delves into the specifics of local appearance-based methods, key-points-based techniques, and hybrid approaches, providing comparative analyses of their efficacy. Moreover, the paper discusses the challenges faced by face recognition systems, recent technological advancements, and potential future trajectories in the field. In essence, Kortli's survey presents a comprehensive and insightful examination of face recognition systems, serving as a valuable resource for researchers and practitioners in the biometrics and face recognition technology sector.

Ting Chen[31] presents a significant advancement in face recognition technology, addressing its applicability across governmental and commercial domains. Despite the successes of existing methods, challenges persist in recognizing faces under varying conditions such as light, expression, posture, and occlusion, with complex illuminations posing particular difficulties. Chen introduces the Neighbourhood Weighted Average Local Binary Pattern (NWALBP), which extends the traditional LBP operator to better capture pixel pair correlations within neighbourhoods. Additionally, the Center Symmetric NWALBP (CS-NWALBP) reduces computation complexity by comparing weighted average values of symmetrically positioned neighbourhood pixels. The proposed CS-NWALBP+HOG fusion algorithm combines the strengths of NWALBP with Histogram of Oriented Gradient (HOG) features, resulting in improved robustness under complex illumination conditions. Experimental results underscore the effectiveness of these algorithms compared to contemporary methods.Summary of the latest literature is mentioned in abstract format in the following table

Table 1: Methods. Summary of the latest literature

Author Name	**Year**	**Techniques Used**	**Main Contribution**
Vijaya et al	2023	CS-NWALBP+HOG	Introduced CS-NWALBP+HOG, a feature fusion algorithm for robust face recognition under complex illumination conditions. Achieved improved performance compared to existing algorithms.
Shahina et al	2023	Laplace of Gaussian, Discrete Wavelet Transform, Discrete Cosine Transform, Multiclass SVM	Proposed a hybrid biometric software application for facial recognition considering uncontrollable environmental conditions, achieving high accuracy and performance.
Sajjad et al	2023	Deep Learning, Transfer Learning, CNN, LSTM, Inception, ResNet, VGG, Xception,	Developed a hybrid model for face recognition using various deep learning and transfer learning techniques

		InceptionResnet	achieving high accuracy.
Hicham Benradi et al	2023	HOG, SIFT, Gabor, Canny, CNN, Softmax, Segmoïd, Adam, Adamax, RMSprop, SGD	Proposed a novel approach to enhance facial recognition accuracy under varying conditions using feature extraction and CNN architecture, achieving up to 100% accuracy in simulations.
Ram Krishn Mishra et al	2022	Deep Learning, Transfer Learning	Proposed a Deep Hybrid Learning (DHL) approach for facial expression recognition achieving 81.42% testing accuracy and 95.93% training accuracy.
Ting Chen et al	2021	NWALBP, CS-NWALBP, CS-NWALBP+HOG	Introduced Neighbourhood Weighted Average LBP (NWALBP) and Center Symmetric NWALBP (CS-NWALBP), proposed CS-NWALBP+HOG fusion algorithm for improved face recognition under complex illumination conditions.
Bui	2021	NWALBP, CS-NWALBP, CS-NWALBP+HOG	Introduced Neighbourhood Weighted Average LBP (NWALBP) and Center Symmetric NWALBP (CS-NWALBP), proposed CS-NWALBP+HOG fusion algorithm for improved face recognition under complex illumination conditions.
Kortil et al	2020	Local, Holistic, Hybrid Approaches	Reviewed face recognition systems, conducted comparative analysis of techniques, highlighted popular face databases, and discussed future directions in the field.
Zhenfeng et al	2020	Deep Learning, CNN, LSTM, HOG, SVM	Developed RFR-DLVT, a hybrid method combining Deep Learning and visual tracking for effective face recognition, achieving high accuracy in real-time FR on surveillance videos.

6. Face Detection and Alignment in Hybrid Models

How Hybrid Models Integrate Face Detection and Alignment Techniques:

Within the sphere of face recognition, achieving precise facial alignment and accurate face detection stands as pivotal stages profoundly impacting the outcomes of recognition tasks. Hybrid deep learning models acknowledge the utmost significance of these initial phases and seamlessly integrate them into their structure.

Face Detection: Hybrid models leverage state-of-the-art face detection techniques to identify and localize faces within an image or video frame. Common methods include Haar Cascades, Single Shot MultiBox Detectors (SSD), and You Only Look Once (YOLO)[29]. These techniques are responsible for identifying the presence and position of faces, providing bounding boxes that encompass facial regions. This information is essential for subsequent processing and feature extraction.

Facial Alignment: After spotting faces, hybrid models make sure the faces are in the right position and look similar. They do this by finding special points on the face, like the eyes, nose, and mouth, and using them to align the faces. They might use methods like Active Shape Models (ASM), Active Appearance Models (AAM)[30], or deep learning-based tools like DLIB to do this. This alignment helps deal with differences in how faces are posed or expressions on the face.

Importance of Accurate Face Detection and Alignment in Face **Recognition:**

Accurate face detection and precise facial alignment are pivotal for several reasons:

Region of Interest (ROI) Extraction: Face detection isolates the region of interest (ROI) containing the face, which significantly reduces computational complexity. This allows subsequent feature extraction and recognition steps to focus exclusively on relevant facial information, improving efficiency.

Normalization: Facial alignment standardizes the orientation and scale of faces. By aligning facial landmarks, hybrid models reduce the impact of variations in pose, ensuring that features consistently represent the same facial attributes across different images.

Improved Feature Extraction: Precise alignment aids feature extraction methods by providing consistent anchor points and reducing noise. This enhances the ability of deep learning models to learn discriminative features effectively.

Robustness: Accurate face detection and alignment make hybrid models robust to variations in lighting conditions, facial expressions, and occlusions. This robustness is crucial for real-world scenarios where such variations are common.

Higher Recognition Accuracy: Face recognition accuracy is directly influenced by the quality of input data. Accurate detection and alignment contribute to cleaner and more informative input, ultimately leading to higher recognition rates.

In essence, the integration of face detection and alignment techniques into hybrid deep learning models ensures that the recognition system can handle real-world variations while maintaining accuracy and robustness. These preprocessing stages are foundational to the success of the recognition pipeline, making them an indispensable part of the hybrid approach to face recognition.

7. Evaluation Metrics for Hybrid Models

There are many different evaluation metrics that can be used to assess the performance of machine learning models. DeMel et Al[9] has briefed the evaluation metrics. Some of the most common metrics for hybrid models include:

● **Accuracy:** Accuracy measures how many of the predictions are right. To figure it out, you divide the number of right predictions by the total number of predictions. accuracy = (true positives + true negatives) / total.

● **Precision:**

● Precision measures how many of the positive predictions were actually correct. To calculate it, you divide the number of correct positive predictions (true positives) by the total of correct positive predictions and incorrect positive predictions (false positives). precision = true positives / (true positives + false positives)

● **Recall:** Recall tells us how many of the real positives were identified correctly. To figure it out, you take the number of correctly identified real positives (true positives) and divide it by the total of those true positives and the ones that were missed (false negatives). recall = true positives / (true positives + false negatives)

● F1 score: The F1 score is like a balanced average of precision and recall. You find it by multiplying precision and recall, then doubling that result, and finally dividing it by the sum of precision and recall. f1_score = 2 * (precision * recall) / (precision + recall)

● ROC curve: The ROC curve shows us the balance between correctly identifying real positives and mistakenly identifying real negatives as positives. True positive rate (TPR) tells us how well it identifies actual positives, while false positive rate (FPR) tells us how often it wrongly labels actual negatives as positives.

The ROC curve can be used to compare the performance of different models. A model with a higher TPR and a lower FPR is considered to be better.

7.1. How to Evaluate Hybrid Models

The previously mentioned evaluation metrics can be applied to gauge the effectiveness of hybrid models in a manner analogous to their application for assessing traditional and pure deep learning models. Nevertheless, when assessing hybrid models, it's essential to take specific factors into consideration. A significant aspect to ponder is the selection of features. Hybrid models frequently employ a blend of traditional and deep features, and this choice can substantially influence the model's performance. Another crucial facet is the fusion strategy, which determines how traditional and deep features are integrated. The choice of fusion strategy can also exert a noteworthy influence on the model's performance.

7.2. Comparison to Traditional and Pure Deep Learning Models

Hybrid models frequently outperform traditional or solely deep learning models[6]. This is due to their ability to leverage the advantages of both traditional and deep learning methods.Traditional techniques often exhibit greater resilience to data noise and variations, while deep learning techniques excel at discerning intricate data patterns. Through the amalgamation of these two approaches, hybrid models can attain superior performance across a broader spectrum of applications.

8. Applications of Hybrid Deep Learning in Face Recognition

In 2023, several cutting-edge applications of hybrid deep learning in face recognition have emerged:

DALL-E 2: DALL-E 2[24] is an advanced language model chatbot created by OpenAI. It possesses the capability to generate realistic images based on textual descriptions, making it valuable for tasks like avatar creation, product design, and marketing material generation.

PEARL: PEARL[25], a hybrid deep learning model from Google AI, excels in identifying individuals in videos, even when they are wearing masks or sunglasses. This technology finds applications in law enforcement and border control.

DeepFace: Developed by Facebook, DeepFace[12, 13] stands as one of the world's most accurate face recognition models. Its applications encompass security, access control, biometric identification, and social media.

These examples represent just a fraction of the latest applications of hybrid deep learning in the realm of face recognition. As technology continues to evolve, we can anticipate the emergence of even more innovative and beneficial applications in the future.

9. Advantages and Challenges of Hybrid Models

Hybrid deep learning models[14] are yielding promising effective results in the Face Recognitio tasks,offering a set of advantages that contribute to their popularity and effectiveness.

Enhanced Resilience[14]: Hybrid models amalgamate the capabilities of traditional techniques with the representational prowess of deep learning. This amalgamation results in increased resilience to variations in lighting, pose, facial expressions, and occlusions, rendering them well-suited for real-world applications.

Enhanced Precision[16]: By harnessing handcrafted features from traditional methods and autonomously acquired deep features, hybrid models achieve superior accuracy in face recognition tasks. This amalgamation enables them to capture both fine-grained and high-level facial attributes.

Efficient Processing: Traditional feature extraction methods are computationally efficient and interpretable[16]. By integrating these methods into hybrid models, computational requirements are frequently diminished compared to pure deep learning approaches. This makes these models more viable for resource-limited settings.

Addressing Potential Challenges and Limitations of Hybrid Approaches:

While hybrid models offer numerous advantages, they are not without their challenges and limitations:

Data Requirements: Deep learning components of hybrid models often require substantial labeled data for training. Acquiring and annotating large datasets can be resource-intensive and time-consuming.

Computational Resources: Deep learning, even in hybrid models, can be computationally intensive, requiring substantial processing power and memory. This may limit their deployment in real-time or resource-constrained environments.

Complexity: The fusion of traditional and deep learning components introduces added complexity to the model architecture and training process, which can be challenging to manage and optimize effectively.

Interpretability Trade-offs: While traditional features offer interpretability, deep learning features are often more abstract and less interpretable. Striking a balance between the two can be challenging, especially when transparency is essential.

Bias and Fairness: Hybrid models are susceptible to inheriting biases present in training data. Addressing issues of fairness, bias, and ethical concerns in face recognition remains a critical challenge, irrespective of the hybrid approach.

Continuous Evolution: The field of deep learning is in a state of continuous evolution. Staying updated with the latest advancements and techniques is essential to harness the full potential of hybrid models.

In conclusion, hybrid deep learning models in face recognition provide a powerful framework that combines the best of traditional and deep learning techniques. Their advantages in terms of accuracy, robustness, and efficiency make them a prominent choice in various applications.

However, addressing challenges related to data, computational resources, complexity, and ethical considerations remains pivotal for their continued development and deployment in responsible and effective face recognition systems.

10. Future Trends and Directions

The domain of hybrid deep learning for face recognition is evolving rapidly, with numerous exciting future trends and directions. Some of these trends encompass:

Advancement of Novel Feature Extraction Techniques: While traditional feature extraction methods like Gabor filters and PCA remain effective, the field is in need of fresh techniques that exhibit greater resilience to data noise and variations.

Exploration of Innovative Fusion Strategies: Fusion strategies, determining how traditional and deep features are combined, present diverse options. The selection of the most suitable strategy for a particular application hinges on specific requirements.

Development of More Efficient Training Methods: The computational expense associated with training deep learning models necessitates more efficient training methods tailored for hybrid deep learning models.

Creation of Models Handling Occlusion and Pose Variations: Occlusion and pose variations are among the most formidable challenges in face recognition. The demand is for models that can more adeptly handle these variations.

Pursuit of Cross-Modal Recognition Models: Cross-modal recognition entails identifying individuals across different modalities, such as face, voice, and gait. Models catering to cross-modal recognition are needed. These represent merely a selection of the numerous future trends and directions within hybrid deep learning for face recognition. As technology continues to advance, we can anticipate the emergence of even more innovative and effective solutions. In addition to the technical challenges, ethical considerations also loom large when developing hybrid deep learning models for face recognition. These considerations encompass:

Privacy: Face recognition technology's capacity to track individuals' movements and activities raises concerns about privacy and surveillance.

Discrimination: The potential bias of face recognition technology against certain groups, such as people of color or women, sparks concerns about discrimination.

Security: The risk of using face recognition technology for creating fake identities or impersonating others underscores security concerns. It's crucial to take these ethical concerns into account when creating and using hybrid deep learning models for face recognition to make sure we use this technology in a responsible and ethical manner.

Conclusion:

This literature review has conducted an extensive examination of the face recognition landscape, with a primary focus on the pivotal role of hybrid deep learning models. These models constitute a fusion of traditional computer vision techniques with the advanced capabilities of deep neural networks, providing a comprehensive solution to the intricate challenges of face recognition. In the sections dedicated to traditional and deep learning techniques, we delved into the historical foundations of face recognition. Traditional methods, such as Eigenfaces, LBP, and HOG, laid the groundwork for comprehending facial features and extracting valuable information. Deep learning, represented by CNNs, Siamese Networks, and FaceNet, revolutionized the field by enabling automatic feature extraction from raw data, resulting in substantial enhancements in recognition accuracy. The review underscored the significance of hybrid deep learning models, highlighting their seamless integration of traditional and deep features. These models harness the merits of both paradigms, offering heightened robustness, increased accuracy, and interpretability. The discussion on key hybrid models, including DeepID, VGG-Face, and SphereFace, showcased their contributions to pushing the envelope in face recognition technology. The section on face detection and alignment recognized these stages as fundamental components within the face recognition pipeline. Hybrid models incorporate state-of-the-art techniques to precisely locate faces and align facial features, ensuring that recognition tasks are executed on standardized, informative facial regions. The advantages of hybrid models, encompassing enhanced robustness, heightened accuracy, and computational efficiency, were emphasized. These models have demonstrated their ability to excel in real-world scenarios featuring diverse challenges. However, the review also acknowledged challenges such as data requirements, computational resources, and ethical considerations, underscoring the imperative of responsible and equitable deployment.

In summation, this literature review highlights the central role played by hybrid deep learning models in advancing the domain of face recognition. Their capability to harness the strengths of both traditional and deep learning techniques has resulted in significant strides in accuracy and robustness. Future research within this domain should continue to explore innovative hybrid approaches, tackle data and ethical challenges, and pave the way for responsible and effective applications across domains like security, surveillance, and human-computer interaction. Integrating interpretability and fairness considerations into hybrid models will be pivotal in ensuring the ethical and responsible utilization of face recognition technology.

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