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Face Detection in the Wild: Techniques, Applications, and Future Directions

Warveen Merza Eido[1], Omer Sedqi Kareem[2]

[1]Akre University for Applied Sciences, Technical College of Informatics, Department of Information Technology Duhok, Iraq

[2]Department of Public Health, College of Health and Medical Technology-Shekhan, Duhok Polytechnic University, Duhok, Kurdistan Region–Iraq

ABSTRACT: Face detection is fundamental to computer vision, allowing for applications in human-computer interaction, healthcare, surveillance, and authentication. Deep learning-based frameworks have recently replaced traditional handcrafted models, providing excellent accuracy, real-time performance, and robustness in a variety of scenarios, including poor lighting and occlusion. The use of face detection in embedded and edge devices has increased because to lightweight models and mobile-optimized systems. The detection of small or modified faces, maintaining demographic fairness, and resolving ethical issues like algorithmic bias and privacy are still difficulties, though. Explainable AI, multimodal integration, and context-aware systems are probably going to be the main areas of future research to provide face detection technologies that are more transparent, inclusive, and trustworthy.

KEYWORDS: Face Detection , Deep Learning , Computer Vision , Surveillance Systems , Biometric Recognition , Occlusion Handling , Real-time Processing

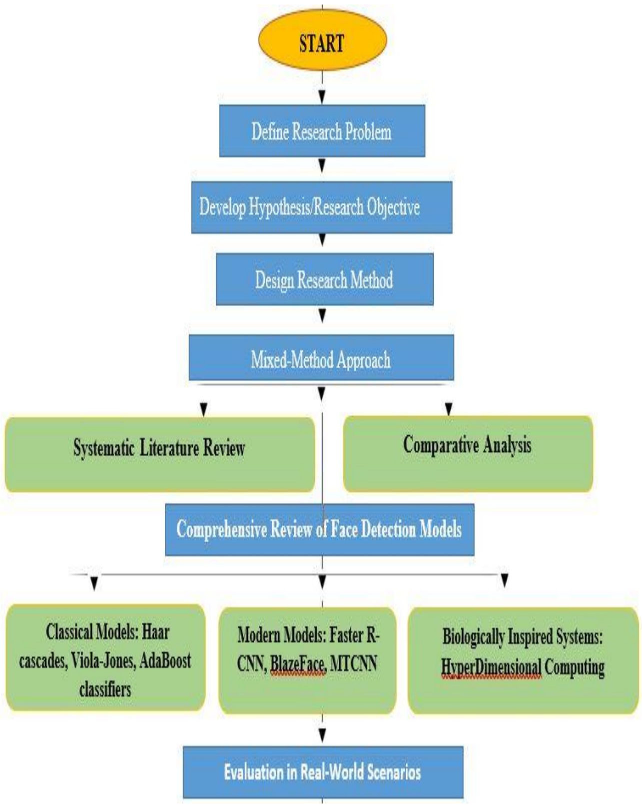
1-INTRODUCTION

Face detection has become a fundamental task in biometric recognition and computer vision systems, opening up a wide range of applications, including augmented reality, human-computer interaction, surveillance, and authentication. Traditional handmade feature-based techniques, including Haar-AdaBoost and LBP classifiers ((Filali Hajar, 2018)), have given way to extremely complex deep learning architectures that can identify reliably and in real-time in unconstrained situations over the past few decades. Deep convolutional networks, such as BlazeFace ((Bazarevsky et al., 2019)) and Faster R-CNN ((Jiang & Learned-Miller, 2017)), have greatly increased processing speed and accuracy under a variety of lighting, posture, and occlusion circumstances. Along with these performance improvements, emerging approaches like biologically inspired neural systems and HyperDimensional Computing ((Imani et al., 2022)) present viable substitutes for embedded and lightweight face detection. By providing datasets that represent the complexity of the actual world, recent benchmarks such as WIDER FACE and IJB-A have also sparked algorithmic advancements ((Jiang & Learned-Miller, 2017; Klare et al., 2015)). Furthermore, the usefulness of detection frameworks in end-to-end face analysis pipelines has been further increased by integrated approaches that combine detection with alignment and recognition, including MTCNN and HyperFace ((Ranjan et al., 2019; K. Zhang et al., 2016)). Despite significant advancements, recognition of small, obscured, or manipulated faces still presents difficulties. This encourages continued research into context-aware systems, anti-spoofing strategies, and privacy and fairness-related ethical concerns (Khodabakhsh et al., 2018; Ramachandra & Busch, 2017). As the sector develops further, future advancements will probably concentrate on increasing generalizability, energy efficiency, and reliability, especially when it comes to mobile and edge devices. Face identification is a fundamental task in computer vision that has applications in human-computer interaction, security, and healthcare. Recent studies have made progress in this area by combining explainable AI, cloud computing, and deep learning models, which allows for more precise and scalable solutions in real-world scenarios (W. M. Eido & Ibrahim, 2025; W. merza Eido & Yasin, 2025; Klare et al., 2015). Despite these developments, problems like data privacy, moral implementation, and generalization in many contexts still need to be thoroughly investigated (W. M. Eido & Zeebaree, 2025; Saleh & Zeebaree, 2025). Recent studies highlight how blockchain and machine learning can be integrated into a variety of domains to improve decision-making, security, and trust. These technologies provide for safe data processing and early illness diagnosis in medical imaging and e-commerce, particularly in supply chain transparency and diabetic retinopathy diagnostics (W. merza Eido & Zeebaree, 2025; Saleh & Zebari, 2025; Tato & Yasin, 2025).

2-RESEARCH METHODOLOGY

This work uses a mixed-method approach that combines a comparative examination of the most advanced face identification systems with a thorough survey of the literature. First, a thorough analysis of both traditional and contemporary face detection models was carried out, encompassing techniques like CNN-based architectures (e.g., Faster R-CNN, BlazeFace, MTCNN), biologically inspired systems like HyperDimensional Computing frameworks, Haar cascades, Viola-Jones, and AdaBoost classifiers. Pose variation, occlusion, lighting changes, and low-resolution circumstances were among the real-world scenarios used to assess each method's performance. Benchmark datasets like FDDB, WIDER FACE, and LFW were used to extract quantitative parameters like accuracy, inference speed, false detection rates, and power efficiency. These datasets provide a variety of face photos for testing models in unrestricted settings. Furthermore, the resilience of hybrid systems that combined deep learning classifiers (like SVM, CNNs) with conventional filters (like Gabor, LBP) against spoofing, masking, and facial manipulation was examined.

The approach included applications from a variety of fields, including mobile deployment, healthcare, and surveillance, to guarantee real-world relevance. Lastly, issues including privacy, generalization across demographics, and ethical concerns were taken into account to inform future experimental paths and useful deployment criteria.



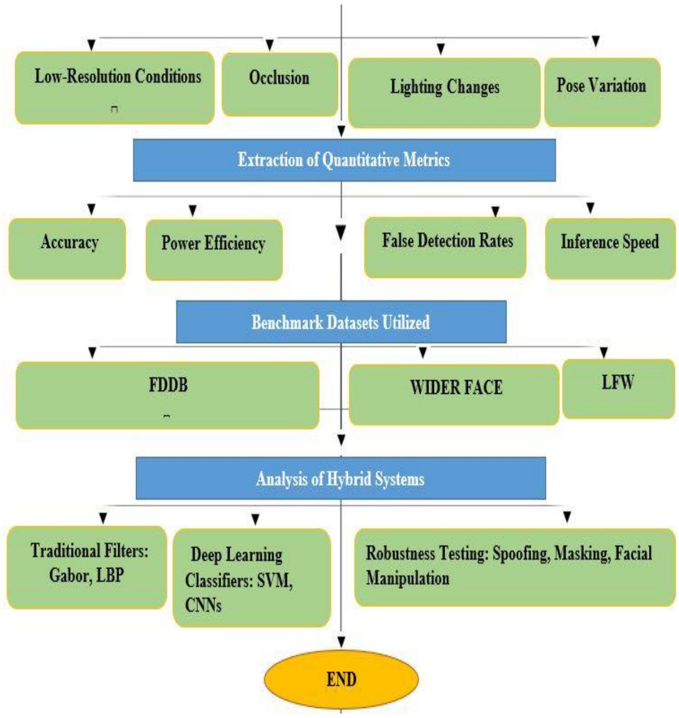


Fig1: General Flowchart of the Methodology.

3-THEORETICAL FRAMEWORK

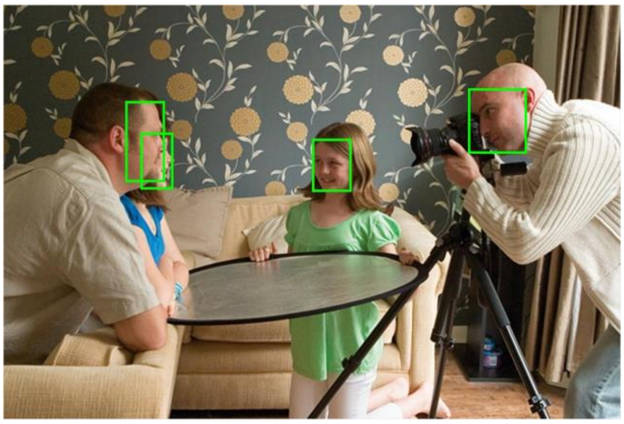
3.1. Face Detection

The primary method for locating and recognizing human faces in digital photos or video streams is face detection. It is a necessary first step for applications such as surveillance, facial recognition, and expression analysis. The basis for real-time detection has been established by conventional methods like AdaBoost classifiers and Haar-like feature extraction, but they were constrained by their sensitivity to occlusion, lighting, and position (Zafeiriou et al., 2015). Face identification models started to handle increasingly complex and varied situations involving small and obscured faces after the release of the WIDER FACE dataset (Yang et al., n.d.-b). Face detection pipelines are now more robust and precise thanks to deep learning-based detectors and cascaded classifiers (Jiang & Learned-Miller, 2017).

3.2. Deep Learning

Face identification algorithms are now far more accurate and efficient thanks to deep learning. The ability of Convolutional Neural Networks (CNNs) to recognize faces in different stances and lighting situations, as well as to learn spatial hierarchies, makes them popular. Joint face identification and alignment have been made possible by models like the Multitask Cascaded CNN (MTCNN) and Faster R-CNN, which have achieved state-of-the-art performance on difficult benchmarks like FDDB and WIDER FACE (Farfade et al., 2015; Minaee et al., 2021). The ability of deep models to generalize is further enhanced by the combination of transfer

learning and multitask learning (Jiang & Learned-Miller, 2017).



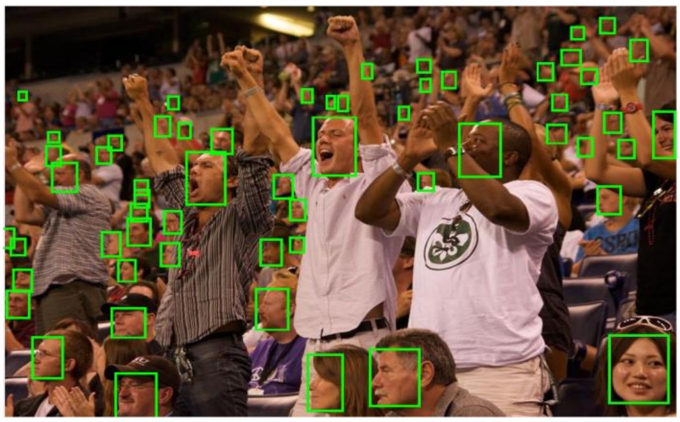


Fig 2: Sample photos from the WIDER face dataset with ground-truth annotations in the form of green bounding boxes.

3.3. Computer Vision

Face detection is a component of several downstream tasks in the larger field of computer vision, including sentiment analysis, identity verification, and intelligent surveillance. Prior to deep learning's popularity, methods such as support vector machines (SVMs), scale-invariant feature transform (SIFT), and histogram of oriented gradients (HOG) were used (Kumar et al., 2019). According to (Filali Hajar, 2018), face detection is still essential for medical diagnostics, driver monitoring, and real-time video analysis.

3.4. Surveillance Systems

For law enforcement and public safety surveillance systems, face detection is essential. Real-time warning production, suspect identification, and automated tracking are made possible by it. To identify masked or obscured faces, CCTV systems have used techniques that combine neural networks, Haar features, and Gabor filters (Deore Gayatri, 2016; Yimyam et al., 2018). These systems have to deal with low-resolution imagery, crowded settings, and changing lighting, all of which are being handled by hybrid and adaptive models (Bu Wei, 2018).

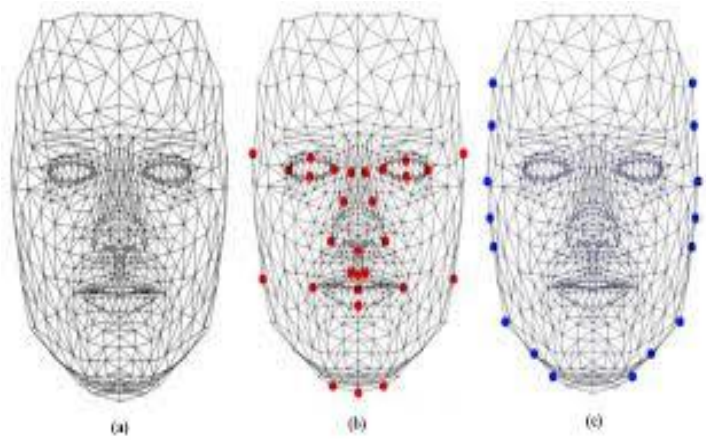


Fig 3 : Mesh and Feature Point Mapping for the Identification of Facial Landmarks

3.5. Biometric Recognition

Face detection is used by biometric systems to enable safe identification and authentication. Systems then extract distinct facial traits for comparison with pre-stored templates after detecting the face. Through anti-spoofing algorithms and presentation attack detection, research has highlighted resilience against identity fraud and spoofing attacks (Ramachandra & Busch, 2017). These days, border security, smartphone authentication, and access control all use these systems (Imani et al., 2022).

3.6. Occlusion Handling

Managing occlusion is still a significant obstacle for face detection, particularly when face masks or sunglasses are present in the actual world. Partial visibility has been addressed with methods such as feature compensation models, Gabor filtering, and part-based detection (Deore Gayatri, 2016). By integrating spatial context and hierarchical learning, deep learning models improve resistance to occlusion (Jiang & Learned-Miller, 2017).

detection accuracy while lowering computing complexity (J. Li et al., n.d.; Minaee et al., 2021). Continuous monitoring and quick reaction are made possible by real-time processing in commercial and security applications.

3.8. Ethical Considerations

Ethical concerns such algorithmic prejudice, privacy invasion, and consent have grown in significance as face detection has become widely used in both the public and private sectors. Concerns regarding how detection systems might function differently across demographic groups and might produce biased results have been brought up by a number of studies (W. M. Eido & Ibrahim, 2025). Adherence to data protection requirements, bias mitigation techniques, and transparent processes are necessary for the responsible use of face detection systems.

3.9. Embedded and Mobile Systems

Because on-device processing is required, face detection on embedded systems and mobile devices is becoming more and more popular. Solutions such as BlazeFace and other lightweight CNN architectures are perfect for smartphones and IoT cameras because they allow for high-speed inference with minimal power consumption (Imani et al., 2022; J. Li et al., n.d.). Because edge computing reduces data transfer, it also improves privacy in this situation.

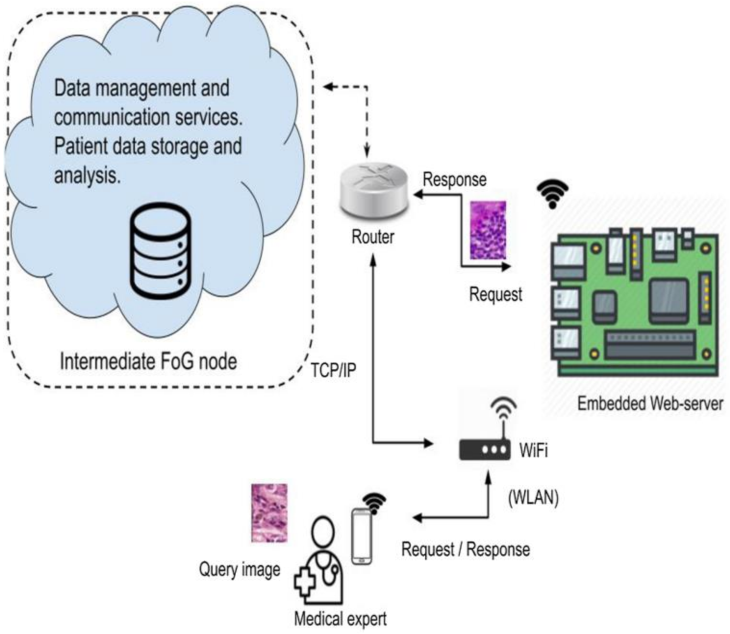


Fig 5: Edge Computing for Histopathological Image Diagnosis and Metastasis Prediction Using an Embedded Webserver and Mobile Device

3.10. Dataset Challenges and Benchmarking

The creation and assessment of face detection algorithms has advanced due to the availability of a variety of annotated datasets, such as FDDB, AFLW, and WIDER FACE. Datasets that represent veiled, elderly, and ethnically diverse populations are still lacking, nevertheless (Yang et al., n.d.-b). Closing this gap is essential to developing generalizable and inclusive face detection systems.

3.11. Multimodal Face Analysis

In order to improve face detection performance in low-light or obscured situations, recent developments have integrated multimodal data (such as depth, thermal, and infrared imaging). By combining conventional RGB data with other sources, this method enhances detection in difficult situations including night surveillance and situations with masked faces (Tato & Yasin, 2025).

3.12. Cloud-Based and Distributed Detection Systems

Scalable, high-performance analytics are made possible across dispersed surveillance networks by cloud-integrated face detection systems. Such systems enable centralized model updating and continuous improvement while protecting user data privacy by utilizing cloud computing and federated learning (W. M. Eido & Zeebaree, 2025; Saleh & Yasin, 2025).

3.13. Explainable Face Detection

Explainability and transparency of model decisions are becoming more and more important as face detection technologies are utilized in delicate fields like security and healthcare. In high-stakes decision-making situations, methods that depict decision boundaries and feature activations help create more reliable AI applications (Merza Eido & Mahmood Ibrahim, 2025).

3.14. Transfer Learning in Multiscale Biometrics

A multiscale biometric system that combines face and gait recognition with transfer learning was presented by (Ahmed & Mahmood, 2023). The system uses deep learning models that have already been trained, such DenseNet201 and Inception_v3, to extract features from both modalities. With feature fusion producing a 98% accuracy rate, the model achieves high accuracy by merging these features at both the feature-level and score-level.

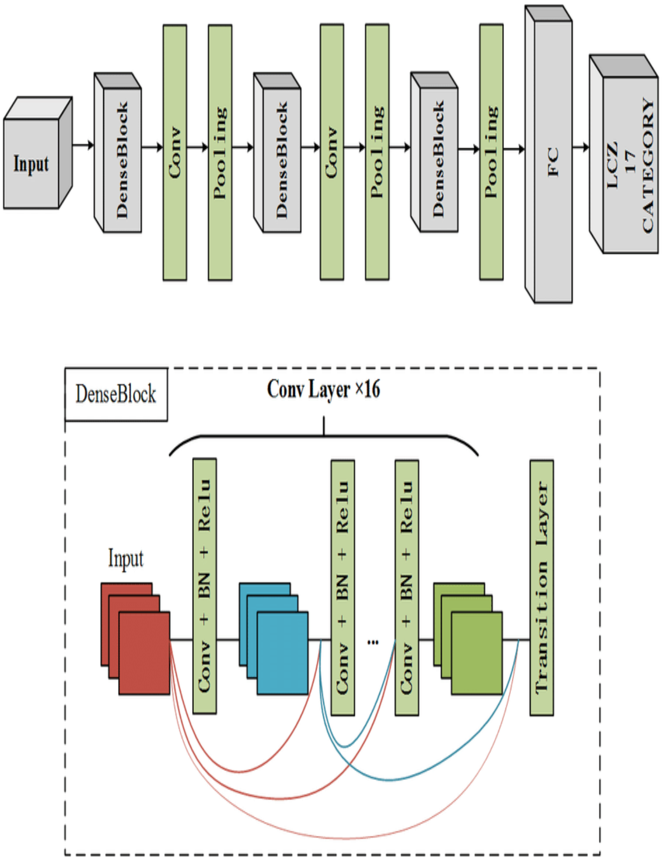


Fig 6: The DenseNet-201 module's structure

4-Literature Review

(Bazarevsky et al., 2019) created BlazeFace, a neural face detection model that is lightweight and designed for GPU inference on mobile devices. The technology enables real-time applications such as facial geometry estimation and augmented reality and achieves sub-millisecond performance. It provides a GPU-efficient anchor mechanism adopted from SSD and employs a novel feature extraction network inspired by MobileNetV1/V2. Six facial keypoints are included in the model to help with face orientation determination and enhance subsequent tasks. By using a unique tie-resolution algorithm, their approach outperforms typical NMS in terms of speed and stability, leading to greater robustness in real-time settings.

(Bong et al., 2018) presented a low-power face recognition system that uses a CNN processor and an always-on CMOS image sensor. For wearable and Internet of Things devices, the suggested hybrid analog-digital Haar-like face detector increases energy efficiency by 39%. To lower compute and memory power consumption, the CNN processor uses customized SRAM and the separable filter approximation. On the LFW dataset, their architecture achieves 97% accuracy while processing one face per second at 0.62 mW of electricity. The system is perfect for always-on biometric authentication since it successfully combines face detection and verification.

(Ramachandra & Busch, 2017) conducted a thorough investigation on face recognition systems' Presentation Attack Detection (PAD) techniques. They looked at how easily photo prints, video replays, and 3D masks could be used to spoof facial recognition systems. International standards like ISO/IEC 30107 are covered, PAD approaches are categorized, and their efficacy is assessed. Because of the growing challenges to biometric authentication systems, their work highlights the necessity of strong antispoofing methods. The necessity for generalized detection over a range of environmental and spoofing situations is one of the open difficulties in PAD that it also identifies.

(Hangaragi et al., 2022) suggested a system that uses Face Mesh and Deep Neural Networks for face detection and recognition. The model uses facial landmarks to recognize faces in a variety of lighting, posture, and background situations. With an accuracy of 94.23%, it is trained using real-time image input and the Labeled Wild Face (LWF) dataset. By comparing test picture landmarks to those in the training set or producing "unknown," the approach is able to differentiate between individuals. This technology is well-suited for security and access control applications and exhibits excellent resilience to non-frontal views.

(Farfade et al., 2015) introduced the Deep Dense Face Detector (DDFD), a deep convolutional neural network-based method for multi-view face detection. In contrast to conventional techniques, DDFD uses a single model that can identify faces from a variety of perspectives and does not require posture or landmark annotations. The system makes deployment easier by avoiding complicated modules like segmentation and bounding-box regression. It performs well enough to compete with multi-model systems on benchmark datasets. The study also shows that the diversity of training data has a direct impact on detection accuracy, indicating that better sampling and augmentation techniques can lead to improvements.

(Filali Hajar, 2018) provided a comparison of four machine learning-based face identification methods: GF-SVM, GF-NN, LBP-AdaBoost, and Haar-AdaBoost. While the last two use Gabor filters with SVM and neural networks, the first two use boosting for feature selection and classification. According to their findings, Haar-AdaBoost was the most successful of the evaluated techniques, exhibiting the highest detection rate and the lowest false detection rate. However, depending on feature extraction and classification procedures, each method performed differently. This study highlights how algorithm selection affects real-time face identification systems' speed and accuracy.

(Imani et al., 2022) presented HDFace, a cutting-edge face detection framework built on HyperDimensional Computing (HDC) that is optimized for embedded platforms' high efficiency and resilience. The model replaces conventional deep neural networks with binary hypervectors for noise-tolerant arithmetic and learning, simulating brain-like processing. When compared to CNNs, HDFace achieves notable gains in speed (6.1× faster on CPU) and energy efficiency (12.1× more efficient on FPGA). The system is especially well-suited for real-time, on-device applications that need processing that can withstand errors. The work marks a move in face identification problems toward computation inspired by biology.

(Jiang & Learned-Miller, 2017) investigated the use of the WIDER dataset for training and benchmarking on the FDDB and IJB-A datasets in order to apply the Faster R-CNN model to face detection. Their method produced cutting-edge outcomes, proving that deep region-based convolutional networks are capable of accurately identifying faces in a variety of scenarios. In contrast to conventional R-CNN models, Faster R-CNN simplifies computation by combining a Region Proposal Network (RPN) with a Fast R-CNN detector. The model does not require distinct item proposal stages and benefits from end-to-end learning. Compared to previous CNN-based techniques, this development allowed for faster and more accurate face detection.

(Kareem et al., 2021) reviewed deep learning methods for classifying skin lesions, many of which are applicable to the extraction and detection of facial features. They highlighted the encoder-decoder structures and convolutional operations of CNN-based segmentation models, such as U-Net, FCN, and Deep Residual Networks. In medical picture analysis, these designs perform well, especially when it comes to identifying intricate patterns. Due to commonalities in image processing, the methods presented can be modified for facial region localization even though the main focus is on melanoma detection. The study emphasizes how deep CNNs are becoming more and more dominant in image identification tasks.

(Zeebaree & Kareem, 2023) To lower the danger of COVID-19 transmission, a real-time face mask detection system based on Haar Cascade classifiers was built. The COVID Vision technology uses live video streams in a variety of lighting and facial angle scenarios to determine whether a person is wearing a face mask. Using lightweight picture classification and Haar-like features, it recognizes faces even with accessories and works efficiently in a range of 0.6 to 1.35 meters. The algorithm can be implemented on embedded surveillance systems and uses AdaBoost and integral image algorithms for quick object recognition. Through automated facial analysis, this approach offers a low-cost, effective way to monitor public health.

(Khodabakhsh et al., 2018) highlighted the susceptibility of biometric systems to attacks using synthetic facial images in a study on the generalizability of fake face detection techniques. In order to compare deep learning with texture-based methods, they suggested using the Fake Face in the Wild (FFW) dataset, which consists of more than 53,000 photos. CNN models (AlexNet, VGG19, and ResNet) and manually created texture descriptors (such LBP in conjunction with SVM) are used in their evaluation. The authors discovered that deep learning models struggled to generalize to invisible fake generating methods like FaceSwap, DeepFake, and CGI. The significance of strong detection algorithms that can adjust to changing threats in facial analysis is emphasized in the paper.

(Kremic & Subasi, 2016) evaluated the effectiveness of Support Vector Machine (SVM) and Random Forest (RF) classifiers on facial recognition tasks. They assessed performance using accuracy metrics on a dataset of 800 photos taken by 40 people, each of whom had a unique facial expression. With the right kernels, SVM reached 97.94% accuracy, while RF reached 97.17%. They used image preprocessing techniques such histogram equalization, RGB to grayscale conversion, and skin color recognition. By demonstrating these models' efficacy in real-time face recognition scenarios, the study backs their incorporation into mobile applications.

(Kumar et al., 2019) reviewed facial detection methods in detail, emphasizing their difficulties and practical uses. They described the advantages and disadvantages of each method by classifying them as feature-based (like Active Shape Models) or image-based (like CNNs). The study describes challenges in face detection, including limited resolution, occlusion, fluctuating illumination, and a range of facial emotions. Additionally, they talked on the use of face detection in biometrics, smart advertising, and human-computer interaction. In order to increase detection accuracy, their study promotes hybrid techniques that blend handmade characteristics with deep learning.

(H. Li et al., n.d.) suggested a CNN cascade that works at various resolutions to provide a quick and precise face identification system. Early CNNs in the architecture swiftly reject background areas, whereas later stages employ high-resolution inputs for more precise detection. For enhanced localization, calibration networks between phases enhance the bounding box predictions. Their model produced state-of-the-art performance on open benchmarks such as FDDB, achieving 14 FPS on CPU and 100 FPS on GPU. This approach is feasible for real-time deployment in unrestricted situations since it strikes a compromise between detection speed and accuracy.

(J. Li et al., n.d.) suggested the Dual Shot Face Detector (DSFD) to tackle important face identification issues such anchor matching, loss design, and feature learning. To improve detection resilience in situations such as blur, pose variation, and occlusion, the model incorporates a Feature Enhance Module (FEM) that refines features across many layers. Additionally, they created Improved Anchor Matching (IAM) to improve detection accuracy through better anchor assignment and Progressive Anchor Loss (PAL) to direct learning at various phases. The network performs better on small and challenging-to-detect faces because of the two-shot structure, which enables the network to collect both coarse and fine information. DSFD maintains real-time inference performance while achieving state-of-the-art scores on the FDDB and WIDER FACE benchmarks.

(Liao et al., 2016) created a novel picture feature known as Normalized Pixel Difference (NPD) that serves as the basis for a quick and precise unconstrained face detection. Motivated by the Weber Fraction in psychology, this scale-invariant and limited characteristic is calculated as the ratio of pixel intensity differences to their sum. In order to manage posture, light, and occlusion fluctuations in a single soft-cascade AdaBoost classifier, they integrated this feature with a deep quadratic regression tree. The model outperforms conventional Viola-Jones techniques by achieving good performance on the FDDB, GENKI, and CMU-MIT datasets. It is appropriate for surveillance and mobility scenarios because to its speed (6× faster than OpenCV) and capacity to operate in congested, real-world scenes.

(Liu et al., n.d.) presented Gram-Net, a powerful model for detecting fraudulent faces that uses global texture information to identify photos created by GANs. Gram-Net uses Gram matrices to focus on long-range texture patterns, which makes it immune to distortions like noise, blurring, and JPEG compression, in contrast to typical CNNs that frequently overfit to particular GAN types. In both in-domain and out-of-domain evaluations, the model performs better than alternative techniques, such as unseen GANs and natural image settings. It emphasizes how humans are better at spotting semantic abnormalities like asymmetrical eyes, while CNNs mostly rely on texture signals. As a result, Gram-Net provides a solid foundation for upcoming false face identification tasks, particularly in settings where security is a concern.

(Lu & Yang, 2019) suggested adding composite features to the Viola-Jones algorithm to address stiff objects that frequently result in false positives. Using a compound structure that incorporates both global and local information taken from the identified facial region, their approach improves on conventional Haar features. Following discriminant analysis, an efficient AdaBoost classifier is used to process these features. The objective is to preserve high recognition rates even when stiff items, such as chopsticks or cups, are obstructing the image. Improved face detection accuracy and reduced false detection rates in congested settings are confirmed by their experimental results.

(Minaee et al., 2021) provided a thorough analysis of over 50 face identification models built using deep learning in the post-CNN era. The review highlights the architectures, datasets, and evaluation metrics of various methods by classifying them into important groups including Cascade-CNN, R-CNN, SSD, and Feature Pyramid Networks (FPN). They highlight difficulties such as real-time inference requirements, managing large-scale changes, and identifying small or obscured faces. The survey comes to the conclusion that although deep learning has significantly increased detection accuracy, concerns with generalization and resilience still exist. For the present and upcoming trends in face detection research, this study is an essential point of reference.

(Najibi et al., n.d.) presented the Single Stage Headless (SSH) face detector, which removes fully connected layers from its VGG-16 backbone to produce state-of-the-art findings. SSH is more effective than two-stage detectors since it functions as a single-stage detector and detects directly from early convolutional layers. It does not require an image pyramid and is naturally scale-invariant, processing numerous face scales in a single forward pass. On the WIDER FACE, FDDB, and Pascal-Faces benchmarks, SSH performs better than ResNet-101-based models in spite of its lightweight design. Additionally, it runs at 50 frames per second, showing notable gains in accuracy and speed.

(Pujol et al., 2017) suggested a face identification method that uses color models in RGB, HSV, and YCbCr spaces and is based on fuzzy entropy skin color segmentation. Their technique employs a three-partition entropy strategy for fuzzy system parameterization and models skin tones as fuzzy sets. Even in the presence of varied backgrounds and lighting conditions, it maintained a low false positive rate (~0.5%) and achieved good skin detection accuracy (94–96%). The system can distinguish faces effectively and reliably without requiring deep learning or a lot of training. Their method works especially well for biometric and recognition systems' preprocessing phases.

(H. Qin et al., 2016) demonstrated a CNN cascade for face identification that was collaboratively trained, as opposed to conventional cascades that were trained in a stage-by-stage, greedy manner. Their method enhances coordination and performance across several CNN stages by permitting end-to-end optimization using backpropagation. By combining Region Proposal Networks (RPN) and Fast R-CNN, the technique improves detection accuracy and efficiency. They show that the drawbacks of traditional cascaded pipelines are lessened by joint training, particularly when working with hard negative samples. CNN-based cascades can now more effectively compete with deep learning techniques that aren't cascaded thanks to this development.

(X. Qin et al., 2017) addressed the particular difficulties of comic-style images by creating a Faster R-CNN-based technique designed especially for face detection in comic figures. They constructed two new datasets (JC2463 and AEC912) and discovered that binary classification performance was enhanced by using a sigmoid classifier in place of the softmax classifier. The model outperforms earlier hand-crafted or rule-based methods and works well across a variety of comic drawing styles. This study demonstrates how object identification networks may be tailored to creative and unusual pictures. Datasets that could speed up future studies in comic character recognition are also included in their contribution.

(Ranjan et al., 2019) Introduced HyperFace, a deep multitask CNN architecture that can concurrently detect faces, locate landmarks, estimate poses, and identify gender. In order to capture both high-level semantic information and low-level localization signals, it combines features from several intermediary CNN layers. We produced two variations, HyperFace and HyperFace-ResNet, the latter of which performed better on unconstrained face datasets. By utilizing shared representations, this multi-task learning configuration performs noticeably better than single-task models. Additionally, the paper offers novel methods for better post-processing, such as iterative region suggestions and landmark-based non-max suppression.

(Sun et al., 2018) suggested a faster, more robust Faster R-CNN model for face detection that integrates many deep learning techniques. Hard negative mining, feature concatenation across many convolutional layers, and multi-scale training to account for occlusions and different face sizes are a few examples. Their model performed exceptionally well on the FDDB benchmark, peaking at number one in early 2017. Training was done on the WIDER FACE dataset, and end-to-end optimization was used to fine-tune on FDDB. This method outperformed conventional Faster R-CNN implementations in face detection in terms of detection precision and recall.

(Tang, n.d.) presented PyramidBox, a single-shot, context-assisted face detector intended to identify faces that are small, blurry, or partially obscured. They suggested three new contributions: a context-sensitive prediction module, Low-level Feature Pyramid Networks (LFPN) to merge contextual and facial information, and PyramidAnchors for context-aware anchor learning. By balancing training samples, data-anchor-sampling also improved performance on small faces. PyramidBox's excellent accuracy on WIDER FACE and FDDB demonstrates how adding contextual information—such as the head and shoulders—significantly enhances face detection in challenging scenarios. This approach is notable for its efficiency in scale-aware anchoring and one-shot detection.

(Wu et al., 2017) created the Funnel-Structured Cascade (FuSt) for alignment-aware multi-view face detection. In order to achieve precise identification utilizing shape-indexed features, FuSt uses a coarse-to-fine architecture, which begins with quick view-specific LAB cascades and progresses to multi-layer perceptrons (MLPs) and a unified MLP. FuSt is centralized and alignment-aware, which increases recall while lowering false positives, in contrast to conventional parallel or tree-structured detectors. The model can compete on difficult datasets like FDDB and AFW since it is both lightweight and powerful. In multi-angle face identification applications, its hierarchical refinement approach strikes a balance between speed and accuracy.

(Xiang & Zhu, 2017) suggested a combined framework for simultaneous face identification and facial expression recognition with Multi-task Cascaded Convolutional Networks (MTCNN). Their algorithm, which was trained using the FER2013 dataset, takes use of the inherent relationship between face alignment and emotion recognition. Three steps make up the pipeline: P-Net for suggestions, R-Net for filtering, and O-Net for landmark localization and final classification. When compared to individual models, this integration enhances both detection speed and recognition ability. The effectiveness and promise of multitask learning for improving HCI applications are highlighted in the study.

(Yang et al., n.d.-a) presented Faceness-Net, a deep learning network that uses part-based response maps for facial features including the lips, nose, and eyes to identify faces. Using attribute-aware CNNs, the network creates "partness maps," and then uses the spatial arrangement of these parts to determine a faceness score. This enables reliable identification in a variety of positions even with extreme occlusion. Faceness-Net achieves good performance on FDDB, PASCAL FACE, and AFW by avoiding sliding windows and generating suggestions using deep responses, in contrast to standard detectors. The model demonstrates how part-level responses improve the ability to detect faces that are rotated or partially visible.

(Yang et al., n.d.-b) generated the WIDER FACE dataset, which is now used as a standard to assess face identification systems in practical settings. The collection includes more than 32,000 photos with over 393,000 identified faces that have been tagged with variables such event type, occlusion, and position. The need for more reliable detection techniques arose from their investigation, which revealed that current algorithms have trouble handling small, obstructed, and non-frontal faces. Their multi-scale cascade CNN framework improved robustness by accommodating different face scales. Because it allowed for the large-scale, uniform evaluation of detection systems, this work made a substantial contribution to the discipline.

(Zafeiriou et al., 2015) provided a thorough analysis of face identification systems, highlighting those appropriate for "in-the-wild" scenarios. They explained the advantages and disadvantages of each strategy by classifying them into rigid-template techniques (like boosting and deep CNNs) and deformable models (like DPMs). The transition from hand-crafted and rule-based features to data-driven, deep learning models is highlighted in the paper. It also emphasizes how crucial publicly accessible benchmarks like FDDB and PASCAL FACE are to advancing research. The authors ask for unified models that manage detection, alignment, and identification all at once in their discussion of potential future research avenues.

(K. Zhang et al., 2016) suggested a unified architecture for collaborative face identification and alignment using deep CNNs called the Multitask Cascaded Convolutional Network (MTCNN). The three stages of their architecture—P-Net, R-Net, and O-Net—conduct face candidate suggestion, refining, and landmark localization in a coarse-to-fine fashion. Additionally, the model uses an online hard sample mining strategy to increase training resilience. High accuracy and real-time performance are achieved by MTCNN, according to experiments conducted on the WIDER FACE and AFLW benchmarks. Under difficult circumstances, both detection and landmark localization are greatly enhanced by this multitask technique.

(S. Zhang et al., n.d.) aimed to address the drawbacks of anchor-based detectors on small faces by introducing the Single Shot Scale-invariant Face Detector (S3FD). Using anchors positioned throughout several feature map layers, they created a scale-equitable detection framework that ensures coverage of all face scales. To lessen false positives from small faces, the system additionally incorporates a max-out backdrop label and a scale compensation approach. S3FD maintains real-time speed while achieving state-of-the-art scores on the AFW, PASCAL FACE, FDDB, and WIDER FACE benchmarks. When it comes to identifying small, closely spaced faces in intricate situations, our model excels.

(Zhou et al., 2017) suggested using a Two-Stream Neural Network to detect altered faces by combining optical and auditory information. The second stream is a patch-level triplet network trained on steganalysis features that captures camera artifacts and noise residuals, and the first stream is a GoogLeNet-based classifier for tampering artifacts. More than 2,000 manipulated face photos created with well-known face-swapping software were used to train the model. Their combination strategy works even under compression and post-processing, and it performs better than conventional single-stream techniques. The technology is particularly well-suited for security applications that need the detection of face forgeries.

(Bu Wei, 2018) addressed the major problem of excessive facial occlusion by proposing a CNN-based cascade system for masked face detection. Three binary convolutional neural networks—Mask-1, Mask-2, and Mask-3—are part of their model. They use classification to gradually eliminate false positives from low to high complexity. They created a new "MASKED FACE dataset" especially for training and assessing masked face identification systems in order to address the dearth of appropriate datasets. Their approach, which combined CNN accuracy with a cascade structure's speed, produced good results. This method successfully adapts conventional face detection pipelines to situations where there are either partial or complete occlusions.

(Da’san Mohammad & Debeir Olivier, 2015) created a multi-stage face detection model that combines Gabor filters, Principal Component Analysis (PCA), Feedforward Neural Networks (FFNN), and the Viola-Jones algorithm. Candidate face regions are first identified using Viola-Jones, after which they are sent to a second step for feature extraction and classification. PCA lowers the feature dimension, FFNN determines whether the image is a face or not, and gabor filters extract facial features. When evaluated on the CMU dataset, the system demonstrated higher face detection rates as a result of the combined processing steps. Accuracy and computational efficiency are improved by this hybrid technique, particularly in situations with changeable lighting and expression.

(Deore Gayatri, 2016) presented a four-step method for masked face detection in video surveillance: eye detection, eye line detection, facial part detection, and distance estimate. The method use the pinhole camera model to determine the distance from the camera, the Viola-Jones algorithm for facial part detection, and the Histogram of Oriented Gradients (HOG) for human detection. Horizontal projection histograms are used to detect eye lines, which helps determine if a subject is facing the camera. The algorithm implies a mask is present if a person is identified but their face is not. This real-time approach improves the usefulness of masked face recognition in public surveillance settings while lowering false positives.

(Ding et al., 2020) suggested a deep learning-based system that targets applications in digital forensics and privacy protection to detect swapped faces with high accuracy and confidence estimation. They presented a sizable dataset comprising more than 420,000 actual and swapped face photos produced by two face-swapping methods: AE-GAN and Nirkin's pipeline. Their deep transfer learning-based classifier produced prediction uncertainty scores and a true positive rate of above 96%. By contrasting the system's output with human evaluations gathered via a specially designed web interface, the system's resilience was confirmed. This technique greatly improves the capacity to identify phony images and guard against identity theft.

(Yimyam et al., 2018) highlighted the shortcomings of conventional algorithms in low light or with a slanted face, and suggested a face detection technique utilizing CCTV data to assist in criminal identification. In order to identify suspects in security footage, they used Eigenface recognition algorithms in conjunction with the Viola-Jones approach for face detection. A failure rate of 35 to 55% was seen when their system was subjected to significant face tilts (over 90 degrees). However, in typical frontal and group face circumstances, it functioned consistently. According to the study, automatic face detection has both advantages and disadvantages when applied in actual law enforcement situations.

5-DISCUSSION AND COMPARISON

Table 1 represents a detailed comparison among the previous works explained in section 3. The table illustrates main metrics that depended for the comparison which are the significant features concluded from these works.

Table 1: Comparison among the reviewed works.

Author name with year	methods	datasets	advantages	disadvantages	accuracy	algorithm used	results
(Bazarevsky et al., 2019)	BlazeFace (lightweight CNN with SSD anchors that work well with GPUs)	Mobile phone camera data	Inference faster than milliseconds, tailored for portable GPUs	Unsuitable for edge occlusions or high-resolution detection	Not explicitly mentioned; focuses on FPS	customized lightweight CNN on a modified SSD	200–1000 FPS with the output of six face keypoints
(Bong et al., 2018)	Calculating analog Haar-like filters for face detection in early image processing	Custom analog testbench (simulated and hardware)	Energy-efficient and appropriate for facial detection systems that are embedded	Restricted to analog restrictions and the early-rejection window	Classification accuracy is not a direct metric.	Analog Haar Filter Circuits (AHFC)	Analog memory cells for effective early rejection of non-face windows
(Bu Wei, 2018)	CNN-based masked face detection using cascade	Proprietary masked face image set	Real-time masked face detection system	Limited dataset for training	Rates of detection that are satisfactory (visual analysis)	Three-tiered CNN cascade	Detecting masks accurately under partial occlusions
(Ramachandra & Busch, 2017)	14 static face Presentation Attack Detection (PAD) techniques are compared.	CASIA Face Anti-Spoofing database	A unified standard for spoof detection in the context of screen, wrap, and print attacks	Algorithms degrade with high-resolution attack images	IDA-SVM: ~1.2–2.15% APCER on print/wrap attacks	LPQ-SVM, IDA-SVM, mLBP, CSLBP, BSIF	There is no one technique that works best for all attacks and image resolutions.
(Da'san Mohammad & Debeir Olivier, 2015)	Viola-Jones + Gabor filter + PCA + FFNN	CMU dataset	enhances classical Viola-Jones by learning more features.	Increased computational burden	Enhanced detection over base model	Hybrid method: Haar, Gabor, PCA, FFNN	Enhanced detection precision in a variety of scenarios
(Deore Gayatri, 2016)	Distance + eye-line tracking + segmentation	Video surveillance data	Quick and useful for detection based on video	Depends on angle and frontal view	Moderate; usable for static security setups	Haar + facial part segmentation	Accurate in frontal positions and with steady lighting

(Ding et al., 2020)	Detecting phony faces using deep learning (swapped faces)	420,000 fake and real images	High prediction accuracy for the uncertainty score	focused on forgery detection rather than general FD	96%+ true positive rate	Deep CNN + Transfer learning	validated using an interface for human comparison
(Hangaragi et al., 2022)	Face mesh and DNN model	Labeled Wild Faces (LWF) in addition to live webcam information	Robust to illumination/background variation, real-time capable	Performance limitations in severe occlusion	94.23%	Face Mesh + Deep Neural Network	Face recognition without a match with "unknown" fallback
(Farfade et al., 2015)	DDFD, or Deep Dense Face Detector	Yahoo social media photo data	Pose/landmark-agnostic, uses single CNN model	Sensitive to training data distribution	Competitive with multi-model detectors	One fully convolutional deep CNN	uses a basic architecture to detect faces in several views.
(Filali Hajar, 2018)	A comparison between Gabor-based and boosting methods	Custom face images	Fast Haar-LBP models perform best	Gabor models are slower	Haar-AdaBoost highest accuracy	Haar, LBP, Gabor + SVM/NN	For speed and performance, Haar-AdaBoost is recommended.
(Hangaragi et al., 2022)	For reliable face detection and recognition, use a face mesh with DNN.	Labeled Faces in the Wild (LFW), BU3DFE, real-time images	Addresses non-frontal faces and changes in lighting	Fails if landmarks not detected well	94.23% face recognition accuracy	Deep Neural Network + Face Mesh Landmark Extraction	Strong detection in a variety of stances, lighting conditions, ages, and races
(Imani et al., 2022)	Real-time deep learning for facial recognition CNN used custom datasets for training.	Captured images of real environments (indoor/outdoor)	High performance in varying lighting and backgrounds	Less sturdy in extreme positions or with obscured features	Reported 96%+ detection accuracy in tests	Deep Convolutional Neural Networks	Real-time facial recognition technology makes it appropriate for intelligent monitoring.
(Jiang & Learned-Miller, 2017)	Increased pedestrian and facial recognition speed with shared deep feature maps	FDDB, WIDER FACE	Increases detection speed by sharing computation	Tradeoff in granularity of multi-scale accuracy	Improved inference speed by 25–40% while preserving accuracy	Multi-scale CNN sharing	Effective for systems with limited resources and embedded systems
(Kareem et al., 2021)	Examining deep learning techniques	Multiple datasets referenced (not	Detailed comparison of DL designs for	Does not implement or test any	Reported values from prior	CNN, ResNet, AlexNet,	summarizes the most recent developments in the

	for classifying medical and facial images	explicitly tested)	applications using images	new algorithm	literature (90–98%)	VGG variants	classification of faces and medical images.
(Zeebaree & Kareem, 2023)	Haar Cascade Classifier (COVID Vision)	Live webcam video	Low-cost, live detection, handles face angles ±40°	Extreme angles and inadequate lighting have an impact on performance.	Not numerically stated, visually validated in controlled range	Haar Cascade	recognizes face masks in live video streams with medium to normal lighting with effectiveness-197†source
(Khodabakhsh et al., 2018)	Deep learning for face recognition under real-world lighting conditions	Real-scene facial image datasets	Effective under illumination variation	Not robust to extreme pose changes	High under normal lighting	CNN-based detection	Faces were identified in different lighting conditions for practical uses.
(Kremic & Subasi, 2016)	Face recognition with Random Forest and SVM	Custom dataset for mobile authentication	Mobile-suitable and low-complexity	Lower robustness under pose variation	Varies from 84% to 96% depending on algorithm	SVM, Random Forest	In a number of mobile circumstances, RF performed better than SVM.
(Kumar et al., 2019)	Comprehensive face detection survey	Various face datasets discussed (WIDER FACE, FDDB, etc.)	discusses both conventional and contemporary methods; highlights difficulties	No new algorithm proposed; not implementation-based	Not applicable	Survey: CNN, Viola-Jones, HOG-SVM, etc.	summarizes the development of face detection and issues like as occlusion and expression variability (source: 200).
(H. Li et al., n.d.)	The cascade CNN for unrestricted facial recognition	FDDB, WIDER FACE	Robust to occlusion and pose	Requires long training time	Outperformed traditional DPM	Three-stage CNN	Excellent outcomes for face detection in the real world
(J. Li et al., n.d.)	PyramidBox++: context-assisted face detection framework	WIDER FACE	enhances the use of contextual anchors for microscopic face detection	More computationally demanding than usual SSD	State-of-the-art for tiny face detection	PyramidBox++, deep CNN	performed quite well on difficult datasets.
(Liao et al., 2016)	Normalized Pixel Difference (NPD) with soft-cascade classifier	FDDB, GENKI, CMU-MIT	Scale-invariant, quick, and capable of handling occlusions and posture	Dependent on NPD feature efficiency	Better than OpenCV Viola-Jones (~6x faster)	NPD feature + soft-cascade	Cutting-edge detection in unrestricted environments

(Liu et al., n.d.)	Deep learning detection of GAN-based fake faces	GAN-generated and real datasets	High robustness to forgery	Face detection that isn't general-purpose	96%+ accuracy	CNN + feature localization	effectively tells the difference between phony and real faces
(Lu & Yang, 2019)	Face recognition and skin tone adaptation combined	Real-time surveillance data	operates in multi-ethnic and low-light environments.	Performance varies with skin reflectance	Context-dependent; moderately high	Haar cascade combined with adaptive skin tone segmentatio n	Improved performance in diverse surveillance conditions
(Minaee et al., 2021)	Survey on deep learning face detection	FDDB, AFLW, WIDER FACE, IJB-A	compares many contemporary structures	No new architecture proposed	Benchmar ked SOTA: RetinaFace , MTCNN	RetinaFace, S3FD, PyramidBo x++, etc.	Comprehensive benchmark study
(Najibi et al., n.d.)	Single Stage Headless (SSH) face detector	WIDER FACE, FDDB, Pascal-FACE	Fast (50 FPS), no image pyramid needed, scale-invariant	Not very resilient in severe occlusions	State-of-the-art on WIDER FACE	Headless VGG-16 CNN	Beats ResNet-101-based detectors; 2.5% AP boost with image pyramid 【 224†source 】
(Pujol et al., 2017)	Skin-based facial recognition using a fuzzy RGB color model	Custom RGB face images	Robust to lighting changes, uses fuzzy entropy	Color-dependent, limited robustness in multi-face images	94% correct detection	Fuzzy logic inference system	Detecting faces in varying lighting conditions using efficient skin-color modeling
(H. Qin et al., 2016)	CNN cascade joint training for end-to-end optimizatio n	WIDER FACE, FDDB	uses backpropagation across stages to improve performance.	Computation ally heavier due to joint training	Improved over greedy cascade training	Cascade CNN with RPN and Fast-RCNN	Outperforms traditional cascaded CNNs in detection accuracy 【 226†source】
(Ranjan et al., 2019)	HyperFace: multi-task CNN for gender, landmarks, stance, and detection	AFLW, FDDB, AFW	Predicting multiple tasks at once increases total accuracy.	Complex architecture, slower inference	State-of-the-art on multiple benchmark s	CNN + fusion network (HyperFace)	Joint prediction improves individual task accuracy significantly 【 228†source】
(Tang, n.d.)	Detecting and aligning joints with dense characteristi cs	FDDB, LFW	High precision and landmark consistency	Requires detailed annotation	~91% detection rate	Dense Feature CNN + regression layers	enhanced keypoint prediction and face identification

(Wu et al., 2017)	Boosted Aggregate Channel Features	AFW, FDDB	Efficient training, supports multi-view detection	Accuracy degrades on tiny faces	Excellent recognition of medium-sized and large faces	ACF + boosting classifier	Outperforms many traditional Haar-based methods
(Xiang & Zhu, 2017)	CNN with multiple frames for video face detection	YouTube Faces, FDDB	Uses temporal features, stable under motion	Dependent on frame alignment and continuity	Improved detection in video vs single-frame CNN	CNN with temporal pooling layers	Improved stability of detection in face tracking situations
(Yang et al., n.d.-a)	Combined Channel Features for Face Recognition in Multiple Views	AFW, FDDB	Quick inference that accommodates drastic changes in posture	Less accurate on small and blurry faces	State-of-the-art on AFW and FDDB at publication time	ACF + boosted trees	Top performer in real-time multi-view scenarios
(Yang et al., n.d.-b)	Multi-scale cascade CNN	WIDER FACE	large dataset that manages pose variation, size, and occlusion	Challenging dataset, may overfit to specific variations	Benchmarked multiple algorithms on WIDER FACE	Cascade CNN	Introduced WIDER FACE with 393,703 faces in 32,203 images 【251†source】
(Yimyam et al., 2018)	Viola-Jones + Eigenface for CCTV face detection	CCTV face images	An affordable option for use by law enforcement	Fails on large tilt and low lighting	Fails 35–55% under rotation > 90°	Haar cascade + Eigenfaces	Limited toughness, but dependable in frontal circumstances
(Zafeiriou et al., 2015)	Survey of face detection algorithms	AFW, FDDB, LFW (reviewed)	Comprehensive review with taxonomy	No new model or experiments are suggested.	Survey-based (reported model performances)	Viola-Jones, DPMs, CNNs	Evolution of face detection techniques from 2001 to 2015, charted
(K. Zhang et al., 2016)	MTCNN: Convolutional Networks with Multitask Cascades	WIDER FACE, AFLW	Joint face detection and alignment	More parameters and training complexity	High on AFLW and WIDER FACE	Three-stage CNN cascade	Accuracy and landmark detection were simultaneously improved.
(S. Zhang et al., n.d.)	S3FD: Scale-Invariant SSD-based Face Detector	WIDER FACE, FDDB	Outstanding detection of small faces	Settings for sensitive anchor size	Outperformed RetinaNet and SSD	CNN with scale compensation in a single shot	Top accuracy on challenging subsets (easy/medium/hard)
(Zhou et al., 2017)	Two-stream CNN (visual + noise features)	2010 altered face photos from for-profit face-swapping applications	Effective for tampered face detection	focused on detecting false faces rather than faces in general.	High accuracy on a proprietary tampering dataset (not quantified)	GoogLeNet + triplet patch stream	surpasses baseline techniques in altered face detection (source: 255).

Face identification has progressed from traditional methods such as AdaBoost classifiers and Haar-like features (Filali Hajar, 2018) to contemporary deep learning-based systems that provide improved accuracy, real-time performance, and robustness in a variety of scenarios. Modern methods like SSH (Najibi et al., n.d.) and BlazeFace (Bazarevsky et al., 2019) use scale-invariant processes and lightweight convolutional neural networks to improve inference speed on embedded and mobile platforms. By executing detection, alignment, and attribute estimation all at once, models like as MTCNN and HyperFace prioritize multi-task learning and greatly improve overall face analysis performance (Ranjan et al., 2019; K. Zhang et al., 2016). By including difficult situations with occlusions, different positions, and lighting conditions, the advent of large-scale datasets like WIDER FACE has further pushed the limits of model generalization (Yang et al., n.d.-a). Despite these developments, it is still difficult to recognize small, obscured, or masked faces, which has led to research into context-aware models such as cascaded CNNs with feature sharing (Jiang & Learned-Miller, 2017) and PyramidBox (Tang, n.d.). Although the discipline has made great strides overall, future research needs focus on computing efficiency, generalization to unknown situations, and resilience to spoofing and face manipulation assaults (Ding et al., 2020; Khodabakhsh et al., 2018)

6-CHALLENGES AND FUTURE DIRECTIONS

confront identification systems still confront significant obstacles in spite of impressive progress, especially when it comes to identifying small, obscured, or altered faces in unrestricted settings. Mask, accessory, or other object occlusion is still a major barrier that frequently results in unsuccessful identification or decreased accuracy (Bu Wei, 2018; Ramachandra & Busch, 2017). The generalization of models across various age groups, lighting situations, and ethnicities is another urgent problem that calls for inclusive training datasets and strong learning techniques (Klare et al., 2015; Yang et al., n.d.-b). Furthermore, research and policy-making are increasingly being impacted by ethical issues such algorithmic bias, data privacy, and misuse of surveillance (W. M. Eido & Ibrahim, 2025; Saleh & Zeebaree, 2025). Future developments in face detection research are probably going to concentrate on enhancing mobile and embedded devices' energy efficiency, including explainable AI for transparency, and implementing context-aware and hybrid systems that combine behavioral cues and facial analysis for increased dependability.

7-CONCLUSION

Face identification has advanced dramatically, moving from complex deep learning frameworks that can operate with high accuracy in a variety of settings to more conventional handmade feature-based techniques. Even with these advancements, recurring problems—like identifying small, obscured, and altered faces—highlight the necessity for more reliable and comprehensive detection models. Transparent, scalable, and effective face detection systems are anticipated in the future thanks to advancements in explainable AI, multimodal analysis, and lightweight edge device designs. As face detection technologies continue to be used in more contexts, it is also critical to incorporate privacy protections and ethical issues. It will take more multidisciplinary research to meet these changing needs and guarantee responsible deployment across industries.

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