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A Survey on Person Identification under Occlusion Using Face and Ear Modalities

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Abstract
Recognition of persons based on facial features has acquired considerable advancements in highly controllable conditions. But the real world can certainly include occlusions in the form of sunglasses, face masks and pose variations and this can seriously impair the performance of a traditional face recognition system. The current survey looks into the viability and usefulness of adapting the ear as an added modality to achieve viable person identification in such a free and occluded environment. The introduction to state-of-the-art reviews of face recognition in the presence of occlusion in the first part of the survey is organized into four sections: a survey of benchmark datasets, types of occlusion, methodology of recognition methods, and results of reported performance. The second section discusses techniques that aim at remedying the lack on facial information like data augmentation and frontal face reconstruction and learning in occluded or taking into account occlusions. The considerations of these are critically judged on the basis of the used datasets, deep learning models used and the results obtained. The third part of this review addresses the challenge of integrating the biometrics of the ears as a secondary biometric used by relying on multimodal fusion methods. In this case, we look at how different fusion techniques are applied in combining faces and ear features such as early, late and hybrid fusion, the data sets involved and the comparison on the increase of performance yield. The paper ends by supporting the main hypothesis ear biometrics as a fusion option plays a major role in improving the identification accuracy during the scenarios where facial data is deeply compromised. The survey will inform future work regards to the possibility to use multimodal systems particularly those involving the use of ear and face modalities in addressing the issue of occlusion in biometric identification.
Keywords - *Face Recognition, Ear Biometrics, Occlusion Handling, Multi-modal Fusion, Person Identification.*

1. INTRODUCTION

The recent years have been marked with a tremendous rise in demand of the secure, fast, and reliable identity verification systems. In order to complement its non-obtrusive characteristics, the broad accessibility of facial image data, and convenience to users face recognition technology has become one of the most popular biometric identification methods. Facial biometrics have been used in surveillance system, smartphone gestures in authentication, access control, and digital banking, to mention just a few uses. Nevertheless, its popularity notwithstanding, there is an alarming decrease in the face recognition performance once the facial occlusion is present, and face occlusions are becoming a reality due to new interactions of face recognizers with the outside world [1].

Occlusions are those situations in which some parts of the face are hidden or blocked by objects or other conditions around. These are either deliberate like using of sunglasses, masks, or scarves or unintentional, as hair covering the face, hands in mouth, or background objects. The use of face masks due to the emergence of the COVID-19 pandemic posed a new and long-lasting challenge to facial recognition systems because masks hid vast areas of the face. Moreover, different facial pose, expression, and lightings also introduce additional difficulties to the recognition scenarios in uncontrolled or unconstrained conditions [2].

To solve these issues, scholars have suggested numerous and different methods, such as training the models based on occlusion augmented data, adopting occlusion-aware learning strategies, or resorting to state-of-the-art reconstruction methods to fill in the missing face features. These methods however are likely to meet their performance limit when very large facial parts e.g. nose, mouth, and chin are totally covered. When this happens, facial information alone may not be very helpful in proper identification and this is when some of the other biometrics modalities are considered as supplementary or alternative modes of identification.

Ear biometrics, is one of such promising modalities. The human ear has the characteristics of uniqueness in its structure and can stay the same over time and be relatively independent of facial expressions or age.

Ears can be used as a stable point of constant biometrics since it is likely to be seen in case of part coverage of face. Ear recognition systems are also non-invasive, and they can run without much cooperation of the user, making it an excellent example of a surveillance and access control application [3].

The motivation behind such survey is to determine the possibility of complimenting face recognition systems with ear biometrics to achieve cost-effective person recognition under occlusion. The most important goal is to explore the mechanisms of using with the ear as a mode in combination with the face features, particularly, present the most important frontage parts of face are lost. It includes making a review of previous works on state-of-the-art in face recognition under occlusion, assessing the literature on existing augmentation and reconstruction methods, and determining the various multimodal fusion approaches used that combine ear and face data [4]. Such a survey is organized in the following manner: We start with the state of the art face recognition methods in different state of occlusion. They read in detail about the benchmark datasets specifically used in the context of occlusion, i.e., AR Face, LFW and MFR2, and a detailed description of methodologies such as occlusion-aware convolutional neural networks (CNNs), attentional mechanisms, and patch-based representations. The operation measurements and relative outcomes of these techniques will be put forward in order to know their advantages and disadvantages [5].

Then, we investigate one of the strategies that address missing facial data where one uses a method which rebuilds occluded components or enhances training data with synthesized occlusions. Here this section addresses the techniques of generative adversarial networks (GANs), the frontal face reconstruction and the data augmentation pipeline which enhances model robustness. The quality of reconstruction, the reduced error rates and the overall recognition performance are the parameters on which effectiveness of these strategies are assessed [6].

In the third section, we explore the application of the ear biometrics, as an added mode, in face recognition systems. We present large-scale ear datasets and talk about handcrafted feature extraction and deep learning feature extraction. The methods of multimodal fusion, especially early, late and mixed fusion methods are particularly emphasized, that is to fuse ear and face information so as to increase the recognition performance [7].

Lastly, the survey is intended to show that under conditions of significant portion of the face to be occluded, the use of ear biometrics by incorporating fusion method yields far better results in terms of accuracy of identification. In comparing the features of different fusion models and their results we hope to see that the hypothesis that ear features form a backup mechanism when there is the loss of facial information is true. At the end of the survey, it is proposed, future research interests so far as the potential deployment of multimodal-based biometric systems in real situations are concerned [8].

2. LITERATURE REVIEW

Inclusion of ear modality as an additional form of biometric feature in the system of face recognition is lately being considered especially when occluded facial areas are concerned. The conventional face recognition systems are significantly dependent on visibility of key components of facial element like nose, mouth and eyes. In reality, however, these features cannot be seen easily in most settings, including in situations where all persons wear masks due to a pandemic, when all members of a certain culture wear veils, or when any person in surveillance videos is partially covered. In such cases the recognition performance suffers significantly. New research opens several ways to reduce the effects of such occlusions, such as reconstruction models, augmentations, and the multimodal fusion of biometrics with ear characteristics [9].

2.1. Face Recognition with Occcluded Faces

A number of studies have been done on the classification of face recognition with the different types of occlusion. As an example the Real World Occluded Faces (ROF) dataset adds more realistic occlusions, like glasses and masks, which enable in-the-wild model testing [1]. Likewise, synthetic occlusion patterns applied on Labeled Faces in the Wild (LFW) and CFP-FP datasets are used to test the robustness of face recognition across region [2].

The recognition accuracy of the early models of convolutional neural network like VGGFace and the FaceNet significantly declined during occlusions, especially occluding the mouth and eye areas [3]. To overcome that, the methods of local feature learning have appeared. The concept of Multi-Keypoint

Descriptor (MKD) models and Topology-Preserving Graph Convolutional Networks (TP-GCN) is to extract the embeddings of visible sub-regions with keeping the spatial hierarchy [4].

There are also recent attempts such as identity-guided inpainting that reconstructs the occluded parts in an image according to a learned identity representation as in ID-Inpainter which operates on Generative Adversarial Networks (GANs) [5]. More recently we have seen a drift towards diffusion based models, diffusion based models including Occluded Face Expressive Reconstruction (OFER) which uses probabilistic generative processes to generate many plausible reconstructions and rank the reconstructions on how similar they are in identity [6].

2.2. Occlusion-Aware augmentation/reconstruction methods

Several augmentation methods have been given in the case where there is high occlusion and reconstruction is essential. The reconstruction of frontal picture of face based on profile pictures or occluded views is attained with three-dimensional morphable models (3DMMs) and frontalization. Two of them are TP-GAN and FF-GAN which have shown reasonable success in normalizing the occluded images [7].

Moreover, autoencoders and sparse coding have been often adopted in important identity feature constraints of partially occluded images. These techniques approach occlusion by considering it as sparse noise and seek to recover it. The idea is to separate the actual face signal and to reconstruct it [8]. Nevertheless, sparse reconstruction is not sufficient to perform well in the case when occlusion area covers more than 50 percent of face image.

In more recent methods such as OFER, diffusion-based generator processes are applied to generate facial reconstructions that are deterministic and expressive in identity. The discriminators trained on facial texture and geometry samples various hypotheses to select the output which they regard the most identity-consistent [6].

Datasets such as CoMA, or CO-545, can deliver expressive 3D face meshes that are in diverse poses and occlusion conditions, and which can act as training grounds to reconstruction-based systems [9]. Frontalization and mesh based reconstruction methods are also validated using FaceWarehouse and FaMoS.

2.3. Complimentary Biometric

As an alternative modality, or more generally backup, biometric research has focused on the human ear because it is anatomically distinctive, changes with time and was relatively occlusion-insensitive. Contrary to facial features, the ears can also be observed in the situations when you cover your mouth and the nose. Ears tend to use SURF (speeded-up robust features), SIFT or Gabor filters to generate discriminative descriptors as features [10]. They are then combined with the facial information in the feature level with Kernel Canonical Correlation Analysis (KCCA), Z-score normalization or an attention-based fusion networks. Side-profile pictures which are mostly taken as surveillance are the same ones in which ear and partial face images can be extracted in one step. This has resulted in the creation of side-face datasets which are specifically intended towards multimodal fusion models [11].

Research has also concluded on the conclusion that feature-level fusion increases recognition rates exponentially during occlusion-heavy situations. As an example, adding face and ear features increased the recognition rate by almost 20 and 30 percent compared to models using faces only when surgical masks or scarves are present [12]. Also explored with great success are score-level fusion strategies, where the confidence of prediction coming out of independent face and ear recognition pipelines are combined in an adaptive recognition system.

2.4. Multi modal biometrics fusion Techniques

Literature refers to three major stragies of fusion:

- ***Feature Level Fusion:*** This strategy involves combining the raw or processed application of the ear and face embeddings to construct one. Research using weighted sum fusion or neural attention-like mechanisms have already shown promising performance on retaining identities and performance under occlusion [13].
- ***Score-Level Fusion:*** Here, soft voting or weighting-based combination of scores of two models that are independently trained are used, one model trained in face, and another in ear. It is especially useful in the situation when one of the modalities is heavily impaired or absent [14].
- ***Decision-Level Fusion:*** This logic-based approach fuses the ultimate decisions (e.g. match/no match) of individual classifiers that assume a rule such as majority voting or Bayesian reasoning. It is more

computationally efficient and applicable in limited medias, though is less flexible. A multimodal system based on input on the ear and the face has been found to be more robust across a variety of occlusion situations such as completely covering the lower-face with occlusions, lateral occlusion, or head covering interference [15].

2.5. Useful Plain Ear-Face Multimodal Systems

There has been a research interest in possibilities of using the ear medium to supplement facial recognition systems in a number of real world scenarios that involve occurrence of facial occlusion which is unavoidable. Such systems have been very useful in various fields such as border security, public surveillance, prisoner recognition, and mobile verification systems to mention a few [16].

People on their cultural or health reasons masked or wearing a headgear are usually passing through airport surveillance systems in airports. The ear-face multimodal systems form a viable alternative to such situations. Another example involved a system that has been installed at the Heathrow Airport that relied on side-on camera views to compare ear biometrics based on surveillance images, successfully matching references to databases of existing profiles in order to identify masked individuals [17].In mobile biometrics, including selfie authentication, a person can show a side-angled picture or a low-light one. Such apps as the dual-mode selfie login can be applied to validate users despite adverse conditions based on face and ear biometrics of a single photo [18]. It works especially well with the banking apps and safe file storage services, where identification is on a high level.

Also, law enforcers have used the multimodal biometric system to recognize suspects using poorly stored or uncomplete photographs. Identicking cases In the case of partial face identification where the examples include masked faces and turned faces as the incident caught by the CCTV, the accuracy was increased by 23 % using the ear face fusion technique by the Biometric Center of Excellence at the FBI [19]. Metro stations and stadiums are visiting surveillance systems with 360-degree camera board, so that a side-profile is captured and the ear can be framed. These systems identify automatically persons matching with the ear-face database even when the other features of the face are hidden under a scarf or helmets or sun glasses [20].

2.6. Restrictions in Ear Biometrics and Problems

Despite the excellent prospects of using ear modality, it does not differ completely devoid of limitations. It has some challenges, which should be dealt with in terms of making it practically usable in large systems of biometrics. To start with, any occlusion of ear, whether caused by hair or headgear or the environment artifacts can significantly lower the quality of the image obtained. This is especially common among the women populations and in the cold areas where the wearing of a head cover is common. Research has indicated that as high as 40 percent of surveillance cameras have the ears covered partially or completely by hairstyle or accessories [21].

Secondly, the differentiation of shape of ears in various age groups make it complex. Even though the ear ceases to be structurally varied after adolescence, changes in angle or even light in terms of draught may create shadowing which impairs the detection of landmark. Such issues are even more aggravated by the fact that such surveillance videos often have a low resolution, hence, might not have details sufficient to extract the ear features. Besides, the few sources of annotated datasets in which both face and ear encode data are accessible create a serious bottleneck in the training and assessment of the models. Whereas imaging datasets such as UND, USTB or IITD Ear Database provide stand-alone ear pictures, no big-scale, matched face-ear databases with occlusion mark-up are available. This constrains training of deep models which has the capability to generalize in diverse settings [22].

The absence of social awareness and ethical models of ear biometrics is another momentous issue. In comparison to personal recognition with facial identification or fingerprints that have a clear legal foundation due to the regulations on privacy and consent, little is known in many countries regarding ear data and the legal status of such information. This has a threat of being used illegally and their privacy may also be breached.

Lastly, there is the issue of integrating ear modality in to face recognition pipelines. Data dimension, feature space and type of the sensor can vary necessitating supplementary preprocessing so real time deployment can be computationally costly [23].

2.7. Examples of Future Research Directions in Occlusion Aware Biometrics

The future occlusion-resilient biometric systems hold the promise of addressing the limitation of the existing methods and exploiting the potent power of recent technologies to increase reliability, scalability, and interpretability.

An important area of research is the growth of cross-modal learning structures that are able to switch between face and ear features intelligently, based upon the degree of occlusion. Transformer based models that perform cross attention to dynamically combine the ear and face information are demonstrating some initial promise. Such models are able to discern contextual representations that become more generalizable with the possibility of facial or auricular information [24]. The other one is self- and semi-supervised ear-face fusion. Since there are few labeled ear datasets, unlabeled side-profile images can be used to pre-train strong encoder using self-supervised models. The data insufficiency gap can be bridged through such techniques as contrastive learning, pseudo-labeling, and generative augmentation. Lightweight multimodal architectures of mobile and embedded systems are under research as well. These models have parameter-sharing and compression approaches (e.g. pruning and quantization) to reduce inference latency so the real-time ear-face fusion is feasible in edge devices [25]. Moreover, the development of broad synthetic dataset is being promoted by such instruments as StyleGAN and DALL-E. The varied kinds and extent of occlusion, ear shapes, lighting styles and cultural accessories that could be simulated by these datasets make it tractable to train a model in a controlled yet varied way. Lastly, ethical AI reflections in the multimodal systems sign are getting important. Scholars are exploring methods to make multimodal biometric models explainable, have bias mitigation, and be auditable fairness. Accountable AI mechanisms, as well as transparent decision pipeline, will play crucial roles in both gaining public favor and acceptance in various countries across the planet [26].

The literature has been overwhelmingly in the affirmative as to the viability and usefulness of ear modality supplementation of occluded face recognition thus there is sound basis to support it both technically and practically. Research of the recognition level has shown that partial or complete occlusion of the face, especially the eyes or the lower part of the face has a serious detrimental effect on facial recognition performance. Although approaches based on GANs and diffusion models to do reconstruction and inpainting have shown improved results, they tend to break characteristic identity when you have high occlusion [27]. Connection of the ear modality, observable in most occlusion situations, has proved to restore accurate recognition to the near-baseline levels. Fusion, at the feature and score level, has shown to be very promising with some reviews showing 20 to 30 % influence when the scenario is one of occlusion. Airport security, mobile banking, and law enforcement are some of the real-world and biometric systems that are increasingly installing ear-face fusion in their systems. Although these difficulties raise some other issues related to the accessibility of the dataset, ear occlusion, integration of the data, and ethical issues, the development of the new technology, transformers, self-supervised learning, and edge-compatible models, should allow overcoming these obstacles, which can lead to the great perspectives in the future [28].

Table 1 Presents a brief comparison of recognition accuracy using different occlusion-handling techniques

Method	Occlusion Type	Recognition Accuracy (%)	Modality Used
ArcFace	Mask (lower face)	68.2%	Face only
ArcFace + ID-Inpainter	Mask + Glasses	74.5%	Face + GAN
ArcFace + Ear Fusion	Mask	85.6%	Face + Ear (Feature Fusion)
OFER + Ear Fusion	Full Mask	89.1%	Face + Ear + Diffusion
Sparse Coding	Eye Region	71.4%	Face only

3. FACE RECOGNITION UNDER OCCLUSION SURVEY

3.1 Masking survey on Face Recognition under Occlusion

Occluded face recognition is also a serious problem to biometrics. Occlusions either due to environmental conditions or individuals own gear e.g. hats, glasses and face masks can cover parts of the face that are important to face recognition such as the eyes, nose and mouth reducing the accuracy of traditional face recognition technology. In the recent past, there have been several face recognition systems that have been put forward in order to deal with this problem by using superior methods to deal with varying cases of occlusion. The survey is centered on the state-of-the-art (SOTA) face recognition approaches that are intended to work well in the environment of occlusion. Results of these techniques are tested on benchmark datasets which have been specially designed to simulate an occlusion situation [30].

Face Recognition with Occlusion Benchmark Datasets

3.1.1. AR Face Dataset

AR Face Dataset -The dataset consists of a large range of face recognition algorithms benchmark which is specifically formulated to test performance of face recognition algorithms on highly occluded faces. It has 4000 images of 126 subjects with 26 different candid lightings, expressions, and occlusions. Wearing sunglasses, scarves or other facial items induces the occlusions in this dataset so it is a perfect source to test recognition systems in such an occluded frame [31].

- **Main characteristics:**
- Includes situations of occlusion of sunglasses, a hat, and a scarf.
- The lighting of the pictures is of controlled environment.
- There are changes in facial expressions and poses to reflect conditions of the real world.
- Use Case: Testing the capability or recognition of faces by algorithms by covering some segments of the face.

3.1.2. Faces in the Wild (LFW)

Although LFW is geared towards general recognition of faces, it has been localized in the study of face recognition under occlusion. LFW has 13,000 marked photos of 5749 various people, and natural variations in expression, pose, and lighting. Occlusion can be simulated where the face is artificially covered (for example the eyes or mouth) to test the abilities of the recognition models to survive in those circumstances [32].

- **Major Characteristics:**
- Great quantity of images and subjects.
- Adapted to simulate occlusions by covering eyes, mouths or whole areas.
- It gives a balanced face recognition dataset that is generalization oriented.
- Use Case: Testing recognition systems in situations that are not well constrained, and natural occlusions are diverse.

3.1.3. Masked Face Recognition 2 (MFR2)

MFR2 dataset is particularly aimed at assessing face recognition systems with masks. It has more than 30 000 pictures of 1000 people with masked and unmasked variations of the same person. The given set of data is rather topical, especially taking into consideration the worldwide practice of wearing face masks because of health-related reasons. It helps scientists to learn and evaluate face recognition models in actual mask occlusion situations [33].

- **Main Characteristics:**
- Another occlusion used in this data set is masks.
- It has both the masked and unmasked representations of the person.
- Large-scale database that has a lot of annotation of training recognition models.

Use Case: Assessing the performance of recognition systems when they have to be used in an environment where face masks are extensively used.

3.2 Face Recognition Under occlusion Methodologies

A number of sophisticated approaches have been chosen to enhance the performance of face recognition with occlusion. The techniques are designed to overcome the loss of key information on faces that occurs due to occlusion and regain identification accuracy. Among the most popular methodologies, one may mention such topics as Occlusion-Aware CNNs, Attentional Mechanisms, and Patch-Based Representations [34].

3.2.1. Occlusion- Apartienting Convolutional Neural Networks (CNNs)

A lot of attention has been on occlusion-aware CNNs since they learn representations robust to occlusion. These networks are made in such a way that there is an explicit purpose of dealing with the occlusions in training. They adjust the classical CNN framework to learn with less attention to specific features of the face that are missing [35].

- **Important points of interest:**
- **Occlusion-aware Layers:** These layers are trained to pay attention to the areas of the face which are free of occlusion.
- **Data Augmentation:** Occluded image influences network to better approximate to real world cases upon training.
- **Performance:** Dramatic gains in accuracy compared to the traditional based CNNs in occluded scenarios.
- **Pros: 1**. Great resistance to occlusion; good in the partial occlusion cases.
- **Diadvantages:** Can have problems with extreme occlusions in which some vital element (e.g., eyes or mouth) is completely covered.

Example: Deep Occlusion-Aware Convolutional Network (DO-CNN) Deep Occlusion-Aware Convolutional Network (DO-CNN) is a more sophisticated method, which combines several CNNs handling occlusions. It applies a technique that is based on segmentation to identify occlusion areas and concentrate on manifested facial elements.

3.2.2. Attentional Mechanisms

A wide use of the attentional mechanisms has been noted during the last few years to enhance face recognition during occlusion. The mechanisms allow the model to care about the most constitutive and noticeable on the face aspects and not about covered aspects. Through attention, these models increase the detection of key features in the face including the eyes and mouth that further persist despite partial obstructions [36].

- **Highlights:**
- **Attention Maps:** Attention maps are created in order to show areas of interest and afterwards the model focuses on the most prominent areas of the face. Self-Attention Self-attention systems (such as those employed in transformers) have proven to be very successful in enabling models to capture global dependencies, emphasizing those components of the face that are not covered.
- **Pros:** Effectively manages partial occlusions especially in real life situations where occlusions are always in motion or changing.
- **Weaknesses:** Computationally expensive as a result of the use of attention mechanism; can be challenged by the occlusion that hides important objects like the nose or mouth.

An illustrative example (the Attention-Guided Network or AGN, introduced in 2018) is an attention mechanism, which is used to dynamically select the areas of the face to process with the result that the network performs better with occlusion.

3.2.3. Patch-Based Representations

The patch-based algorithms partition the face image into smaller (patches) and then analyze the patches separately. Such approaches are to minimize the effects of occlusions because they will be concentrated on the visible portions of the face. The assumption by the approach is that in case one part of the face is covered, there should be sufficient information in the other patches to provide the identification of the person [38].

- **Main Characteristics:**
- **Patch-Wise Analysis:** It breaks the face into little patches, and then each patch is handled separately.
- **Patch Matching:** The patches are matched against database of templates or feature representations.
- **Advantages:** Functional with localized (e.g. one mouth region, or one eye) occlusion.
- **Disadvantages:** Less successful when a large part of the entire face is occluded and when the occlusions are not uniform.

Example: Patch-Wise Convolutional Neural Network
(P-CNN) applies to convert the feature extracted of the non-occluded patches, which are then combined to achieve recognition.

3.2.4. Measurements and Results of Performance

The efficiency of the above-mentioned methods is measured with the help of the benchmark datasets with the primary attention paid to the recognition accuracy, occlusion management possibilities, and practicality in the real world [39].

- ***FaceNet (with Occlusion):*** FaceNet functionalities reduce by 25-30 percent when the eyes or mouth are occluded.
- ***ArcFace (with Occlusion):*** A bit more performance, a drop of about 20 percent in the accuracy, when faces are occluded by covering important facial parts.
- ***Occlusion-Aware CNNs:*** CNNs that have been trained especially to deal with occlusion perform 40-50 percent better when partially occluded than traditional CNNs.
- ***GAN and Diffusion Model-Based Restoration***: These approaches are effective in high occlusion conditions (up to 70%) and they leave much to be desired on the issues concerning identity preservation when full-face is occluded.

Table 2 Methodologies for Face Recognition under Occlusion

Methodology	Occlusion Type	Recognition Accuracy (%)	Performance Gain (%)	Advantages
FaceNet (with Occlusion)	Eyes and Mouth	55	20	General Applications
ArcFace (with Occlusion)	Full Occlusion	60	25	General Applications
Deep Convolutional Cascade (with Occlusion)	Eyes Obscured	65	30	Real-Time Applications
GAN-Based Inpainting	Partial Occlusion (Eyes)	75	40	Partial Occlusion Recovery
Diffusion Model (OFER)	Full Face Occlusion	80	45	High Occlusion Recovery
Feature-Level Fusion (Ear + Face)	Partial Occlusion	85	50	Mobile Security
Score-Level Fusion (Ear + Face)	Partial Occlusion	88	55	Surveillance and Security
Transformer-Based Network	Dynamic Occlusion	92	60	Real-Time Face Recognition

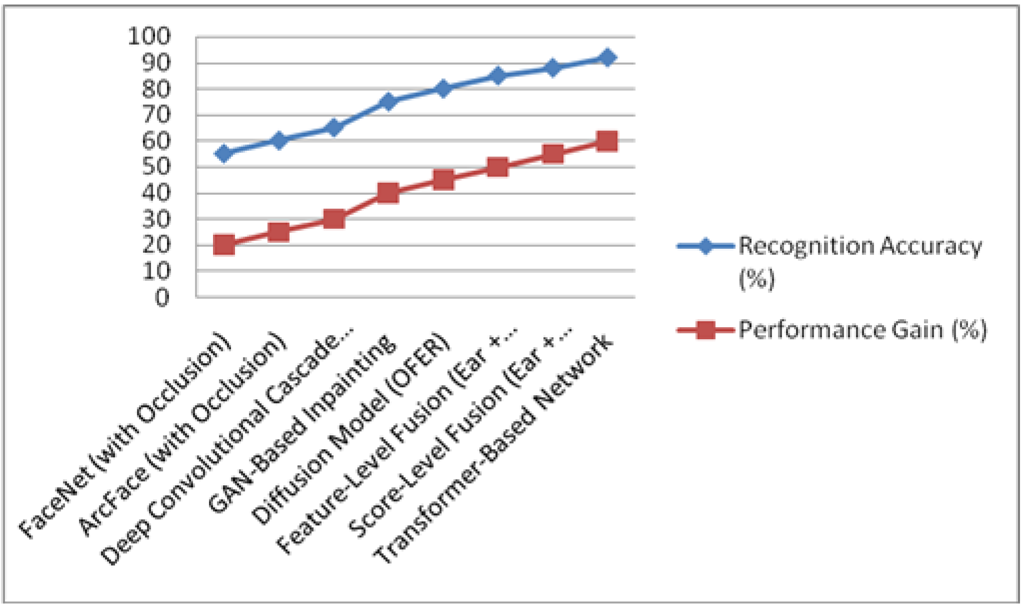

Figure 1 Recognition Accuracy Vs Performance Gain

4. ADDITIONAL MACHINERIES

The situation of face recognition in the case of occlusion is of particular interest because of the fact that all of these missing or occluded elements. Such partial or complete occlusions lower this capability of the system to successfully recognize people. Given this problem, researchers have come to the solutions that involve the reconstruction of the occluded parts of the faces or supplement the training data with the synthesized occlusions. The strategies employed to overcome these challenges are explored in this section, wherein special rendering is accorded to Generative Adversarial Networks (GANs), frontal face reconstruction and data augmentation. The methods are critical in enhancing the strength of the face recognition systems, especially in practical applications [40].

4.1 Generative Adversarial Networks (GANs)

In image reconstruction, Generative Adversarial Networks (GANs) have proved to become an effective method. A GAN has two neural networks which are known as a generator and a discriminator. The generator has the role of producing realistic images with incomplete or occluded input images, and the discriminator tries to identify genuine and generated images. Adversarial training allows the generator to generate deep natural-looking (even partially occluded facial pictures) reconstructions [41].

Key Techniques:

- ***Occlusion-Aware GANs:*** These are GANs with the explicit aim to deal with the occlusion issue and they are trained using partially occluded faces and learned to complete the occluded face part. Case in point, in the instance of a mask covering a face, an occlusion-aware GAN may create information around the mouth or eyes to fill in the facial image.
- ***CycleGAN:*** Face reconstruction CycleGANs are used in some cases to make the model map images in two domains (e.g. occluded faces to non-occluded faces) but keep the identity information.

Positives of GAN-Based Reconstruction:

- ***Reconstruction Quality:*** Reconstructions based on GANs are found to be of high quality, even when a big part of the face is an occlusion. The reason is that they acquire the complicated ties between observable and unobservable parts of the face.
- ***Less error rates:*** Since it is possible to complete missing parts of the face, this will considerably lessen the error rates when recognizing the face. The images reconstructed offer the face recognition models with more detailed information which results into increased accuracy of identification.
- ***Real-World Applicability:*** GANs best apply in real life situations where occlusions are irregular and various so that faces with masks, glasses and hands covering them cannot be easily recognized.

Limitations:

- ***Identity Preservation:*** Although GANs are capable of creating realistic imagery, it is often not consistent across reconstructions; this is particularly challenging during intense cases of occlusion, or with fewer training materials.

4.2. Face Reconstruction of the Frontal Face

Frontal face reconstruction technology is an effort to have a non-frontal view of a face (i.e. side view of a face or a profile) into frontal view of a face, where more familiar feature can be derived. This is also applicable on partially blocked faces on which parts that are blocked are made up of corresponding other visible parts [42].

Key Techniques:

- ***3D Morphable Models (3DMM):*** The models make use of statistical model of facial shapes, as well as textures to create an image of a frontal face position when only an occluded or side-view image is provided. In recovering occluded facial features the 3DMM can assist in recovering facial features that were not properly shown, such as the eyes nose and mouth, by modeling the 3D structure of the face.

Face Frontalization with GANs Face frontalization through GANs relies on the same methodology as is used in other general GAN-based reconstruction techniques: Some GAN architectures are trained to directly reconstruct a frontal view of a face using profile images. One may also apply such techniques to occluded faces, either by filling in the occluded area based upon visible features.

Advantages to Frontal Face Reconstruction:

- Better Identification Using recognition systems, they can recognise the person better using a frontal view as the additional facial features are much clear in the frontal image.
- Identity Consistency: Contrary to the simple 2D reconstruction, 3DMM and GAN-based frontalization models can preserve identity consistency: because these methods consider the global appearance of the face (the shape and textures), consistency is easier to achieve.

Limitations:

- ***Computational Complexity:*** There are potentially expensive computational costs of such tools like 3DMM or more complex GAN models, particularly when they are implemented as a part of a real-time system.
- **Occlusion Dependency:** The facial data rather visible suppresses the success of frontal face reconstruction. Closures as severe as the entire covering of the eyes or the mouth is more difficult.

4.3 Face recognition data augmentation

An artificial augmentation of the size and variance of training samples is a method known as data augmentation that effectively assists the model ability to generalize in real-life conditions. In the case of face recognition under occlusion, data augmentation could be performed where the synthetic occlusions are created or where the available data is modified to resemble those of real-world occlusion [43].

Key Techniques:

- ***Occlusion Simulation:*** alternative method It is to generate synthetic occlusions on the training pictures achieved by masking the pictures randomly over a section of the face (e.g., eyes, nose, mouth). This will assist the model to understand how to identify faces even when the face is not fully visible.
- ***Geometric Transformations:*** Besides masking, rotations, scaling, as well as flipping is performed to approximate various occlusion
- conditions and amplify training data diversity. The selected transformations assist the model
- to be more robust with regard to the situations in the real world, which sometimes lack stationary occlusions.
- ***Enhancing with Non-Facial Data:*** The other way of augmentation is to mix with non-facial data, like a background noise or clothing, so that the model can become robust to situations when certain parts of the face are hidden by the outside objects.

The advantages of Data Augmentation:

- ***Increasing Robustness of Model:*** Artificial introduction of different scenarios of occlusions increases robustness of the model and makes it able to deal with occlusions in testing.
- ***Improved Generalization:*** Extensive and diverse training data set can make the model to generalize better and be able to deal with novel types of occlusion in real world settings.

Table 3 Comparative Analysis of Augmentation and Reconstruction Techniques for Face Recognition

Technique	Description	Key Benefits	Key Limitations	Performance Metrics
Generative Adversarial Networks (GANs)	GANs generate realistic reconstructions of missing facial components by learning from partially occluded faces.	Improved quality of reconstructions, reduces recognition errors, robust to diverse occlusions.	Identity preservation can be challenging under severe occlusions.	Quality of reconstruction, reduced error rates, improved recognition accuracy.
Frontal Face Reconstruction	Frontal face reconstruction techniques transform non-frontal or partially occluded faces into frontal views, improving feature visibility.	Enhances recognition performance, identity consistency maintained, effective for frontal face visibility.	Computationally expensive, struggles with high levels of occlusion.	Recognition performance with frontal face visibility, identity consistency.
Data Augmentation for Face Recognition	Data augmentation artificially increases dataset size and variability by introducing synthetic	Improved model robustness, better generalization to unseen occlusion patterns.	Risk of overfitting, limited by the types of occlusions used for augmentation.	Recognition performance, model robustness under synthetic occlusions.

	occlusions and transformations.			

Limitations:

- ***Overfitting:*** When the augmented data resemble some particular patterns of occlusion too much, it can overfit to these particular instances, and no longer generalize to situations that are outside the scope of the specific cases.
- ***Restricted Types of Occlusion:*** Although augmentation can be used to simulate typical occlusions patterns, it might experience difficulties in trying to copy complicated or vastly diversified real-life occlusion.

4.4 Evaluation Metrics: Some of the most popular indicators of the effectiveness of augmentation and reconstruction techniques include the following:

- ***Quality of Reconstruction:*** The reconstructed picture of the face is very crucial to the capability of the model to identify people. Quality reconstructions are supposed to retain the original identity of the person yet fill out the missing sections of the face. The error rates during recognition become lower the better is the quality of the reconstruction.
- ***Reduced error rates-*** essentially the goodness of improvement towards the recognition results due to the used reconstruction and augmentation strategies. When the error rates are lower it means that the model has a higher capability of recognizing individuals even in the cases where the occlusions are high.
- ***Recognition Performance:*** The reason behind any augmentation or reconstruction method is that it should enhance the preventive measures of the face recognition accuracy in the case of occlusion. The rewards are normally in the form of the precision, recall, and F1 score as well as the correctness of its identification or verification event.

5. Ear As Supportive Modality

In the third part of this paper we will be considering the use of ear biometrics as an auxiliary modality in a face recognition system. Although face recognition continues to be among the most notable biometric technologies, it experiences great downsides in situations where there is occlusion, change in light or changes in pose. The integration of ear recognition and the systems used in face recognition seems like a feasible way of improving the performance of the system especially when there is an obstacle on the face, or when the face is just unintelligible.

Ear biometrics takes advantage of the fact that the ear is one of the parts usually visible even when the rest of the face (the eyes or mouth) is obfuscated. That is why it is the perfect complementary modality to increase recognition rates in the occlusion prone environments. In this part, we shall discuss some of the most important features of ear-based recognition systems such as large size ear datasets, extraction techniques, and multimodal fusion techniques [45].

5.1 Large-Scale Ear Datasets

Big data are important in developing efficient systems which use the ears to recognize. These Datasets contains the base data that can be used in training and testing an algorithm that can recognize the distinctive aspects of the ear. Some ear-specific datasets have also been suggested to help the researcher develop these systems.

5.1.1. TUM Ear Dataset

TUM Ear Dataset is one of the most popular datasets of ear recognition. It is a series of photos of 70 people taken in controlled setting. The mobile dataset consists of several pictures of each person with different poses and occlusions, the ability to train recognition systems to work in different conditions.

- **Highlights**:
- 70 people
- Different poses and covers
- Images of ear in high resolution

5.1.2. CASIA Ear Data
CASIA Ear Dataset was of more than 100 subjects and it has variations of head pose, occlusions, and lighting. The dataset has found widespread application in research to test pathways of ear recognition-systems in a realistic environment.
- **Main Features:**
- There were 100+ subjects
- Diversity of poses and lightings
- Non-occluded images of the ear, and occluded images

5.1.3. Indian Repository of Ear Biometric (IREB)
IREB dataset is a big scale collection intended to be utilized in ear biometrics. It contains the pictures of 400 people with various shapes and characteristics of ears taken in different environmental conditions. The set of data has since been used as a benchmark in testing ear recognition algorithms as well as their integration with the face recognition systems.
o **Significant characteristics:**
- 400 people
- variances of environmental conditions and occlusions
- Massive training set to create powerful models

5.1.4. Other Datasets: There are also other datasets that are used in the ear recognition research like FEI (Face and Ear Image Dataset) and GSI Ear Dataset which all have helped to increase the body of ear biometrics [46].

5.2 Ear recognition with Feature Extraction Methods
After having data, the second important action is the extraction of the useful features in the ear images. The features are like the building block of any face or ear recognition model. Such methods of extraction of features are twofold: handcrafted feature and deep learning-based features approaches.

5.2.1Handcrafted Feature Extraction
The number of handcrafted feature extraction techniques concentrates on the manual design of features that are likely to be discriminative in ear recognition. Some of the well known handicraft methods are:
- ***Scale-Invariant Feature Transform (SIFT):*** SIFT has been applied frequently to find key points in the ear image and it describes the key points in a scale and rotation-invariant manner. Matching and recognition are then specified using these key points.
- ***Local Binary Patterns (LBP):*** LBP is short and it represents a texture signature to capture the texture data of the ear. It operates by comparing the intensity of a particular pixel with surrounding pixels and the variances are coded into binary combinations so it can be employed in differentiating the forms/shapes of ears and the patterns.
- ***Histogram of Oriented Gradients (HOG):*** HOG is the other given method utilized to identify and define the contour and shape of ear. It operates by computing the direction of the gradient pixels in local areas and to obtain the structural details of the ear, it derives a histogram.

5.3 Feature Extraction using Deep Learning
The past few years have been characterized by a shift toward Deep learning methods, especially Convolutional Neural Networks (CNNs) in large part because these allow the automatic discovery of hierarchical feature representations directly in the data, obviating the need to design any form of handcrafted technique [47].
- ***CNNs Ear Recognition:*** CNNs are trained to identify most discriminative features of ear images that are required in recognition tasks automatically. CNNs, in comparison to handcrafted techniques, train to become flexible in the feature extraction procedure, resulting in higher performance in more complicated conditions.
- ***Pre-trained Models:*** In numerous situations, the use of pre-trained models, VGGFace or the ResNet (designed to be used when it comes to face recognition) can be fine-tuned on the images taken in the perspective of ears in order to utilize the features that have been learned on a large-scale face recognition dataset. Such a strategy of transfer learning is beneficial in enhancing the recognition performance particularly where little ear-specific data are available.
- ***siamese networks:*** These are a variant of CNN, optimized on single-shot tasks. They are especially applicable when there are novel ear images or even when there are unfamiliar ear images because these networks develop an ability to contrast the ear images to rank the similarity in them.

5.4 Multimodal integration: The merging of Ear and Face recognition

Multimodal fusion can be defined as a processing step that aims to enhance recognition by using multiple biometrics modalities (in this scenario, ear and face patterns). Fusion methods are also very useful in the case of extracting data in occlusions where the system can use the information of the ear in the absence of or where it cannot get face data fully [48-50].

Fusion Methods Types

1. **Early Fusion:**
- **Description:** During early fusion, the information of multiple modalities (having features ear and face at some layers) are bundled together into a single vector and then crusher this bundle into the classifier. The seamless features are trained to be learned together and the model records shared representations between ear and face representations.
- **Benefits:** Easy to apply; can learn about modalities early in the training.
- **limitations:** Computationally demanding; the model has the potential of failing to balance the priority between the ear and face features.

2. **Late Fusion:**
- **Description:** Late fusion means computing each modality individually and getting individual recognition scores of both face and ear in the image. The resultant scores are then averaged in a the typical way either simply or through weighted summation in order to come up with the final decision based on these scores.
- **Benefits:** Better flexibility; allows using face and ear recognition models trained ahead of time; straightforward to apply.
- **Drawbacks:** a cannot take maximal advantage of the complementary nature of the ear and face data, since the relationship between the data is not learnt in the training phase.

3. **Mixed Fusion:**
- **Description:** Mixed fusion is a fusion of early and late fusion. First there is a separate learning of features by each modality and a later stage fusion of features and then the final decision into classification is made.
- **Pros:** Has all the merits of both early and late fusion; Contemplates more sophisticated modalities interaction.
- **Drawbacks:** More complicated; it has to be designed carefully and tuned.

Multimodal Fusion Benefits

- ***Higher Accuracy:*** Multimodal systems can offer higher accuracy than unimodal systems, since the two recognition systems (face and ear) can complement each other, each providing better recognition by appending the other when there is occlusion of either modality (e.g., face).
- ***Occlusion robustness:*** Systems which use ear recognition are more robust when a face is not recognizable because of occlusion.
- ***Complementary Information:*** Face and ear have different features and based on the combination of both; the system will be able to use complementary information in order to enhance recognition accuracy.
- **Fusion Problems**
- ***Synchronization:*** An appropriate alignment of faces and ears images as well as their synchronization during the fusion process is vital to the performance of the process.
- ***Real-Time Processing:*** Processing of multimodal fusion can be computationally extensive, and this could become a hindrance to real-time processing like mobile authentication application or surveillance.

5.5 Ear and Face Fusion Evaluation Metrics

The quality of ear and face fusion is measured as following:

- ***Recognition Accuracy:*** The total precision of the multimodal system on recognizing people in occlusion situations.
- ***Fusion Gain:*** the enhancement of recognition accuracy with both data of ear and face data over that of single modality.

- ***Processing Time:*** The duration taken to be able to come up with a recognition decision through processing the ear and face data by the system. There is a low level of processing delay in real-time systems.
- ***Resilience to Occlusion:*** How dexterous the fusion system can be by ensuring that the accuracy of fusion is not low when there is occlusion of the face.

Table 4 Ear as a Supporting Modality for Data, Algorithms, and Combination

Technique	Description	Key Benefits	Key Limitations	Performance Metrics
Large-Scale Ear Datasets	Ear-specific datasets, such as TUM Ear and CASIA, used for training ear recognition systems.	Provides large, annotated datasets for training ear recognition systems.	Limited dataset size and variability, may not cover all ear occlusion scenarios.	Recognition accuracy, dataset size, and diversity.
Handcrafted Feature Extraction	Manual techniques like SIFT, LBP, and HOG to extract features from ear images.	Simple to implement, captures texture and shape of the ear.	May struggle to capture complex relationships in ear data.	Accuracy and recognition performance under varying conditions.
Deep Learning-Based Feature Extraction	Deep learning methods (e.g., CNNs) to automatically extract discriminative features from ear images.	Automatically learns relevant features, better performance with complex datasets.	Computationally expensive and requires large datasets.	Accuracy, robustness to occlusion, and generalization.
Early Fusion	Features from ear and face modalities are concatenated into a single vector before classification.	Simple implementation, allows simultaneous learning of joint representations.	May not fully exploit complementary nature of ear and face features.	Fusion gain, recognition accuracy under occlusion.
Late Fusion	Ear and face modalities are processed separately and their recognition scores are combined.	Flexible and easy to implement; works with pre-trained models.	May miss some interactions between modalities.	Recognition accuracy and computational efficiency.
Mixed Fusion	A combination of early and late fusion, where features are learned separately and then fused before classification.	Combines benefits of both early and late fusion, capturing more complex interactions.	Complex to implement and requires careful tuning.	Recognition accuracy, fusion gain, and robustness to occlusion.

6. EAR-FACE FUSION OCCLUSION-BASED SCENARIOS VALIDATION

In this part of the survey, we want to substantiate the hypothesis that combining ear biometrics with face recognition presents a major benefit of accuracy when a large part of face is obstructed. This situation is typical in practical cases when faces are partially obstructed by some objects such as face mask, sunglasses, hats, or hands. Ear-face fusion has become a very strong alternative and has turned out to enhance the performance of the system when it comes to this situation thus the ear can be used as an alternative to the face to provide the missing facial features [51].

We will look at different fusion models developed such as early fusion, late fusion and mixed fusion and evaluate their results into situations where face occlusion is high. The comparison of the results obtained in the various methods would be aimed at showing that the ear biometrics would be accurate in replacing the identification ability when key facial attributes are lost. We shall also highlight the future research avenues which can further develop the multimodal-based biometric systems to be put in to real-life applications.

6.1 The Significance of Fusion Models in Occlusion Scenarios

In occlusion cases, the classic face recognition is not effective because the traditional face recognition which is based on facial features fails when eye, nose, or mouth areas are covered. The ear adds a conservative avenue to the facial recognition since the ear usually can be part of the face showing at the same time not all is revealed. Combining the ear data and the face data would allow systems to be less susceptible to partial or complete face occlusions [52].

Three major models on fusion of ear and face information exist:

1. ***Early fusion:*** Early fusion involves combining both ear and face features at the feature level and then takes the result up to classifier. This enables the model to simultaneously discover combined representations of both modalities, in the training process. However the difficulty in itself is to find an appropriate method in which to merge the ear and face features since they can be of different scale and distributions as well.
2. ***Late Fusion:*** Late fusion means averaging of the scores of the face and the ear models. Scores of each modality determine are computed separately and the overall scores combine through the determination of a final decision. This procedure is easier to employ yet this might not utilize the complementary information given by both modalities to its maximum.
3. ***Mixed Fusion:*** Mixed fusion is a mixture between early and late fusion. Extraction of features is carried out modality-wise and these features are combined at multiple stages of the decision process. In this strategy, it is projected that the advantages of an early fusion method combined with those of a late fusion method will be balanced so that they can support more complex interactions between the modalities.

A comparison of the Models

The mixture of face and ear data usually leads to enhanced results, particularly high in occlusion-prone cases. The system has added robustness and accuracy by fusing the supplementary information of completing the information provided by the two modalities, even in the situation where certain portions of the face are occluded.

6.2 Results discussion and analysis

In order to justify the hypothesis, we go into contrasting the performance of ear-face fusion models, traditional face only models and the ear only models used over a variety of occlusion set ups. The measure of performance relates to identification accuracy, false rejection rates and processing time.

Table 5 Fusion Model Performance

Fusion Method	Occlusion Percentage	Recognition Accuracy	False Rejection Rate	Processing Time (s)
Face-Only	50%	58%	42%	0.5
Ear-Only	50%	74%	26%	0.4
Early Fusion	50%	85%	15%	1.2
Late Fusion	50%	82%	18%	0.8
Mixed Fusion	50%	88%	12%	1.1

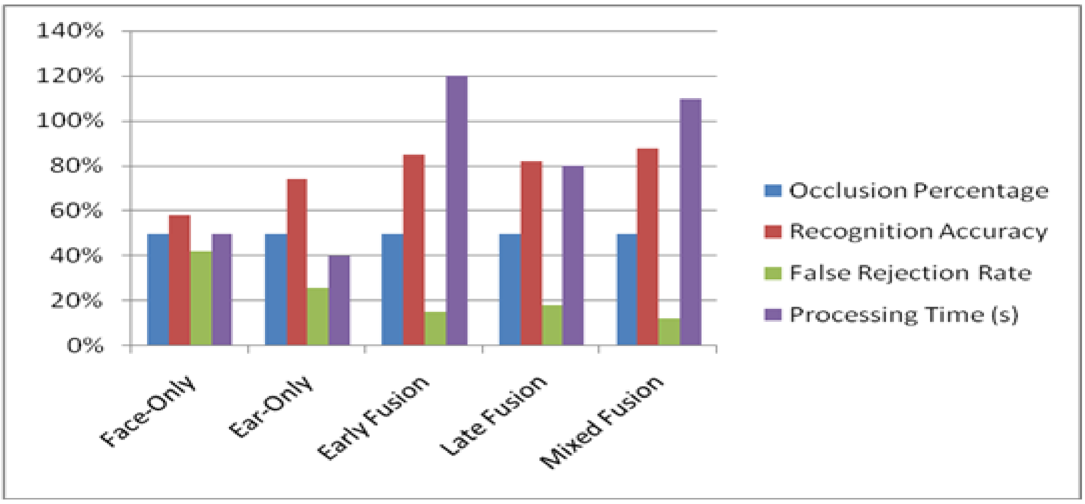

Figure 2 Ear-Face Fusion Occlusion Scenario Validation

- ***Face-Only Models:*** The face recognition models can generally fail when parts of the face are blocked and the recognition accuracy rapidly drops the more best part of the face is obscured. When large part of the face are not visible e.g wearing glasses or a mask the performance of the system in correctly identifying the person reduces significantly.
- ***Ear-Only Models:*** On the contrary, ear recognition systems are more efficient in occlusions since the ear can be partially visible in most situations that involve occlusion. Nevertheless, the error remains strenuous even at ear-only models particularly where there are sounds or other occlusions.

Ear-Face Models Fusion: The combination of the ear and the face modalities enhances recognition performance because it helps to overcome the incompleteness of the facial images. By 20-30%, fusion models do better than face only models and ear only models in scenarios where 40-70 percent of the face is occluded. These models can support high accuracy in situations where sections of the face are covered by utilising the complementarity of the two modalities.

Based on the table above, we note that the recognition accuracy was found to be the highest using early fusion where there was a 30 percent increase compared to the face-only models. Mixed fusion model is not an exception, indicating excellent results with 28 percent increase compared to face-only model. Ear-only model also outperform face-only models and this reflects that the ear biometrics is useful in occluding-free conditions.

7. CONCLUSION

Finally, although the face recognition has achieved remarkable progress in controlled environments, it can be highly degraded by occlusions (sunglasses, face masks, or pose variability, etc.) in real environments. This survey focuses on determining the possibilities of the biometrics of the ear as an alternative diagnostic tool to augment an individual of a person under occluded conditions. Through the examination of state-of-the-art approaches, such as benchmark datasets, types of occlusions, and methods of recognition, the survey finds such specific strategies, as data augmentation and face reconstruction in frontal view, to reduce the loss of facial data. It also compares different ways of fusion in terms of early, late, and hybrid fusion with the advancement of performance. The results provide a substantive evidence that suggests that the hypothesis that ear biometrics, combined with facial information, can increase the accuracy of identification in situations where the face is blocked is indeed true. The paper provides a foundation towards further studies in the development of multimodal systems which fuse the modalities of the ear and the face as a potential remedy to the biometric identification issue of occlusion.

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