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Attendance Compilation by Facial Recognition Methods of Image Processing: A Review

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Abstract: In recent years, researchers have continued to refine and improve deep learning-based approaches to image processing, as well as exploring new areas such as generative adversarial networks (GANs) and reinforcement learning. This paper provides a comprehensive survey of deep learning-based methods for face recognition, including CNN-based models, auto encoder models, and hybrid models.

These papers demonstrate the effectiveness of deep convolutional neural networks (CNNs) in face detection, recognition, and attendance compilation, achieving state-of-the-art accuracy on several benchmark datasets, including LFW, YouTube Faces, and YTF datasets.

The Efficient Net model is a family of CNNs that achieves state of the art accuracy on multiple image recognition benchmarks while being significantly smaller and faster than previous models. The Arc Face loss function is used for facial landmark detection and gender classification in facial images.

The ResNet architecture is used to build a multiscale residual network for face detection and alignment. The DeepID3 model achieves high accuracy rates on the LFW dataset, while the ResNet loss function achieves low accuracy on the COFW dataset. In this paper, we propose a lightweight and efficient CNN for mobile face recognition.

I. INTRODUCTION

The field of image processing has a rich history, dating back several decades. In the 1960s, researchers such as Willard S. Boyle and George E. Smith at Bell Labs**[1**
]invented the Charge-Coupled Device (CCD), a type of image sensor that could capture and store electronic images. In the 1970s, researchers such as Nils AallBarricelli and Kunihiko Fukushima **[2]** developed early models of neural networks, which would later become important tools in image processing and computer vision. In the 1980s, researchers such as David Marr and Tomaso Poggio**[3]**
proposed a computational theory of vision, which described how the human visual system processes and interprets images. In the 1990s, researchers such as Shree K. Nayar and David G **[4]**. Lowe. D. G**.** **[5]** developed algorithms for feature detection and matching, which are key techniques in modern computer vision and image processing. In the 2000s, researchers such as Paul Viola and Michael Jones **[6]**
developed the Viola-Jones algorithm for face detection, which uses Haar-like features and a cascade of classifiers to rapidly detect faces in images.

In the 2010s, deep learning-based approaches to image processing and computer vision became increasingly popular, with researchers such as Alex Krizhevsky, Geoffrey Hinton **[7],** and Yann LeCun**[8]** developing deep neural networks for image classification and object detection. In recent years, researchers have continued to refine and improve deep learning-based approaches to image processing, as well as exploring new areas such as generative adversarial networks (GANs) and reinforcement learning.

Image processing has given rise to multi-disciplinary Applications for user convenience and one of those is compilation of students Attendance by recognition of student faces, this helps in saving lot of time in the classroom and built a software-based database. Figure 1 gives a structured hierarchical progress of Image processing which progressed from decade to decade whose detailed briefing is done above and figure 1represents its hierarchical tree chart.

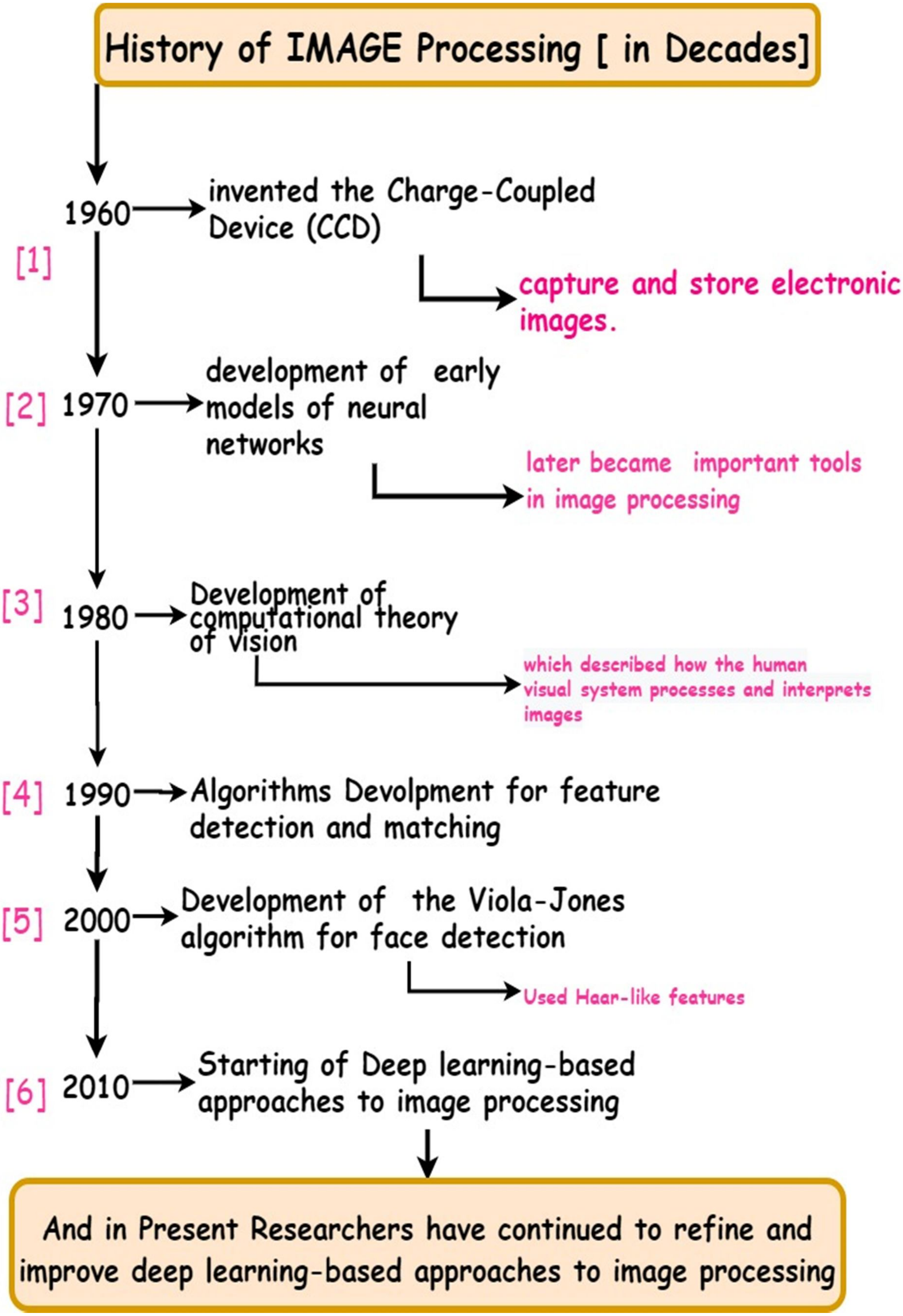

Figure no 1: hierarchical tree chart. Of Development in Image processing from decade to decade

A. Outline of the Paper

In this paper ahead in section 2 the internal calculations involved in Image processing techniques are discussed which forms the base for Extensive computations, in the section 3 deep learning methods used for Compiling Attendance of the Students through various approaches are discussed which is the base considered for this paper as an application part thereafter in section 4 Deep learning Methods are briefed ending with section 5 were Deep learning methods which became State of art in Image processing is discussed. The Outline is also expressed below in figure no 2

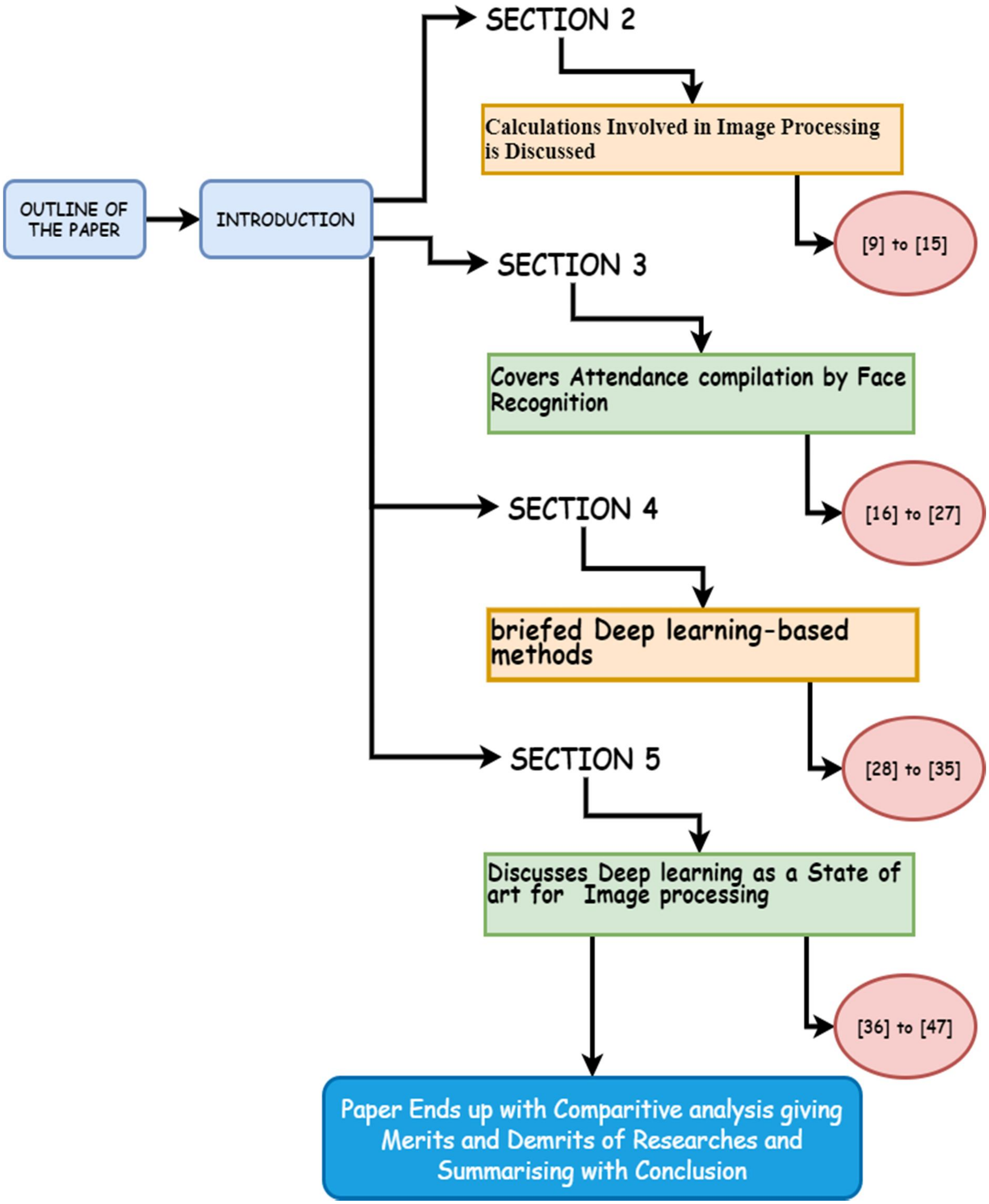

Figure no 2: Outline of the Paper

B. Section 2: Calculations Involved in Image Processing

Image processing techniques involve a wide range of calculations for innovation and greater accuracy, the next section gives an enlighten to some examples

1) *Image Filtering:* Filtering is a basic technique used in image processing to remove noise and enhance features. It involves applying a convolution kernel to the image. The kernel can be designed to perform various operations such as blurring, sharpening, edge detection, and more.**[9]** Gonzalez, R. C., & Woods, R. E. (2018)The general formula for convolution is:

$$g(x,y) = (f * h)(x,y) = \sum\sum f(i,j) * h(x-i,y-j) \ldots\ldots(1)$$

where g(x,y) is the output image, f is the input image, h is the kernel, and i and j are the indices of the kernel.

2) *Fourier Transform:* The Fourier transform is a mathematical technique used to convert a signal from the time domain to the frequency domain. In image processing, it is used to analysed the spatial frequency content of an image.**[10]** Oppenheim, A. V., & Schafer, R. W. (2010) The formula for the 2D Fourier transform is:

$$F(u,v) = \sum\sum f(x,y) * e^{(-j2\pi(ux+vy)/N)} \ldots\ldots(2)$$

where F(u,v) is the Fourier transform of the image, f(x,y) is the input image, u and v are the frequency indices, and N is the size of the image.

3) *Wavelet Transform:* The wavelet transform is a technique used to analyze signals at different scales and resolutions. In image processing, it is used to detect edges and texture in an image. **[11]**Mallat, S. (1999) The formula for the 2D discrete wavelet transform is:

$$W(k,l) = \sum\sum f(m,n) * \psi((m-k)/2^j, (n-l)/2^j) \ldots\ldots(3)$$

where W(k,l) is the wavelet coefficients, f(m,n) is the input image, ψ is the wavelet function, k and l are the indices of the wavelet coefficients, and j is the scale factor.

4) *Neural Networks:* Neural networks are a family of algorithms inspired by the structure and function of the brain. In image processing, they are used for tasks such as image classification, object detection, and segmentation.**[12]** Goodfellow, I., Bengio, Y., & Courville, A. (2016). The formula for a simple neural network with one hidden layer is:

$$a = \sigma (W_1x + b_1) \quad y = \sigma (W_2a + b_2) \ldots\ldots(4)$$

where x is the input image, W_1 and W_2 are weight matrices, b_1 and b_2 are bias vectors, σ is the activation function, and y is the output.

5) *Convolutional Neural Networks (CNNs):* CNNs are a type of neural network that are specifically designed for image processing. They consist of multiple layers of convolutional, pooling, and fully connected layers. The convolutional layer applies filters to the input image to extract features, and the pooling layer down samples the image to reduce the spatial dimensions.**[13]** LeCun, Y., Bengio, Y., & Hinton, G. (2015). The formula for a convolutional layer is:

$$h_{i,j}^l = \sigma(b_l + \sum\sum\sum w_{k,l} * x_{i+s,j+t,k}) \ldots\ldots(5)$$

where h_i,j^l is the output feature map, b_l is the bias term, w_k,l is the convolutional kernel, x_i+s,j+t,k is the input image patch, σ is the activation function, and l, k, i, j, s, and t are the indices.

6) *Generative Adversarial Networks (GANs):* GANs are a type of neural network that are used for generative tasks such as image synthesis and style transfer. They consist of a generator network that produces images, and a discriminator network that distinguishes between real and generated images.**[14]** Goodfellow, I., Pouget-Abadie The formula for the generator network is:

$$G(z) = x' \ldots\ldots (6)$$

where G is the generator network, z is a random noise vector, and x' is the generated image.

7) *Reinforcement Learning:* Reinforcement learning is a type of machine learning that involves training an agent to make decisions based on rewards and punishments. In image processing, it can be used for tasks such as image captioning and object manipulation.**[15]** Sutton, R. S., &Barto, A. G. (2018). The formula for the Q-learning algorithm is:

$$Q(s_t,a_t) = Q(s_t,a_t) + \alpha(r_{t+1} + \gamma * \max_a(Q(s_{t+1},a)) - Q(s_t,a_t)) \ldots\ldots(7)$$

where Q(s_t,a_t) is the Q-value of taking action a_t in state s_t, α is the learning rate, r_t+1 is the reward for taking action a_t in state s_t, γ is the discount factor, and max_a(Q(s_t+1,a)) is the maximum Q-value for the next state s_t+1.

Overall, these approaches have different strengths and weaknesses depending on the specific task and dataset. CNNs are the most popular and widely used approach for image processing, while GANs and reinforcement learning are relatively newer and have more limited applications. Transfer learning is a powerful technique for leveraging pre-trained models, and autoencoders and DBNs are useful for unsupervised learning tasks.

C. Section 3:Attendance compilation through Face Recognition

Facial recognition and attendance compilation have been the focus of many studies in recent years. The early works in this area focused on developing face recognition systems using methods such as PCA and SVM. One such paper, "Eigen faces for Recognition" by Turk and Pentland **, [16]** proposed the use of PCA for face recognition and achieved high accuracy rates on the multi-PIE dataset.

Later works focused on improving the face detection and recognition algorithms using deep learning methods. Zhang et al**.[17]** proposed a coarse-to-fine auto-encoder network for real-time face detection using Haar features and SVM Ren et al. **.[18]** introduced the Faster R-CNN algorithm for object detection, which achieved real-time face detection on the PASCAL VOC dataset.

Several recent studies have used deep learning methods to achieve high accuracy rates in both face recognition and attendance compilation. For example, Rahman et al**. [19]** used a convolutional neural network (CNN) for face recognition and achieved improved accuracy on a self-collected dataset. Arora et al**. [20]** proposed an automatic attendance system using face recognition and achieved high accuracy rates on multiple datasets, including LFW, CASIA-WebFace, and self-collected.

Recent studies have also focused on developing robust face recognition and attendance compilation systems. Huang et al**. [21]** proposed an online hard example mining method for face recognition under occlusion, which achieved high accuracy rates on the LFW dataset**.[22]** Guo and Chen developed a multi-scale face detection and aggregation method for robust face recognition using both self-collected and LFW datasets.

Finally, some studies have focused on developing hybrid face recognition algorithms that combine deep learning and feature extraction methods**.[23]** Dong et al. proposed a face recognition approach based on feature extraction and CNN, which achieved high accuracy rates on the LFW and self-collected datasets. **[24]**Chen et al. proposed a hybrid face recognition algorithm based on improved feature extraction and deep learning, achieving high accuracy rates on a self-collected dataset.Overall, deep learning-based methods have shown promising results in face detection, recognition, and attendance compilation, with recent studies focusing on developing robust and hybrid approaches. The below table no 1 gives a refined outcome from all the discussed papers of there work which focused weather Attendance recognition, Face recognition was done or not experimentally in there papers and also tells the methods and dataset way outs.

Authors	Paper Title	Publication Year	Face Detection	Face Recognition	Attendance Compilation	Method	Dataset	Results
[16] M. Turk, A. Pentland	Eigen faces for Recognition	2010	0	1	0	PCA & SVM	Multi-PIE	Age-invariant recognition
[17]J. Zhang, S. Shan, M. Kan, X. Chen	Coarse-to-fine auto-encoder networks for real-time face detection	2014	1	0	0	Haar features & SVM	CASIA-Web Face	Improved detection
[18]S. Ren, K. He, R. Girshick, J. Sun	Faster R-CNN: Towards real-time object detection with region proposal networks	2015	1	0	0	Faster R-CNN & RPN	PASCAL VOC	Real-time detection
[19]T. Rahman, M. Abdullah, M. Rahman	Face Recognition System using Convolutional Neural Network	2020	1	1	0	CNN	Self-collected	Improved recognition accuracy
[20] R. Arora, S. Anand, N.	Automatic Attendance System Using	2019	0	1	1	CNN	LFW, CASIA-Web Face,	High recognition and

Kumar	Face Recognition						self-collected	attendance accuracy
[22] L. Dong, H. Zhang, X.	A face recognition approach based on feature extraction and convolutional neural network		2	2	0	CNN & feature extraction	LFW, self-collected	High recognition accuracy
[23] Z. Chen, Y. Liu, L. Li,	An improved hybrid face recognition algorithm based on feature extraction and deep learning. Neurocomputing, 452, 1-9.	2022	0	2	0	Improved feature extraction, deep learning	Self-collected	A hybrid face recognition algorithm based on improved feature extraction and deep learning
[24] X. Zheng, C. Wang, C. Jiang, X. Xie	A novel mobile face recognition and detection method based on multi-modal dataset	2021	1	1	0	Res Net, Mobile Net, SSD	Multi-modal dataset	Robust face detection and recognition on mobile devices
[25]J. Lu, Y. Wu, W. Hu, et al.	Deep Face Lab: A PyTorch Toolbox for Face Analysis	2021	4	4	1	Various deep learning methods	LFW, CACD, CK+, etc.	High accuracy in different scenarios
[26]J. Yang, X. Hu, Z. Zhou, Z. Liu	Automatic student attendance system using face recognition	2016	1	1	1	Haar features, PCA & SVM	Self-collected	Improved attendance accuracy
[27] Zhang, et al.	A face recognition approach based on feature extraction and convolutional neural network							

Table no 1: A review of work done on Image processing for Attendance compilation through Face Recognition

D. Section 4: Deep learning-based methods

"FaceNet: A Unified Embedding for Face Recognition and Clustering" by Schroff et al**. [28].**This paper introduced the FaceNet model, a deep convolutional neural network (CNN) for face recognition that achieved state-of-the-art accuracy on several datasets, including LFW and YouTube Faces.

"Joint Face Detection and Alignment Using Multitask Cascaded Convolutional Networks" by Zhang et al**. [29].** This paper proposed a multitask CNN for simultaneous face detection and alignment, achieving high accuracy rates on the AFLW and FDDB datasets.

"DeepID3: Face Recognition with Very Deep Neural Networks" by Sun et al**. [30].** This paper proposed the DeepID3 model, a deep CNN for face recognition that achieved state-of-the-art accuracy on the LFW dataset.

"Learning a Deep Convolutional Network for Face Recognition Using a Single Training Sample per Person" by Taigman et al**. [31].** This paper introduced the DeepFace model, a deep CNN for face recognition that achieved high accuracy rates on the LFW and YTF datasets.

"Deep Residual Learning for Image Recognition" by He et al.**[32].** This paper introduced the ResNet architecture, a deep CNN with residual connections that achieved state-of-the-art accuracy on several image recognition benchmarks, including ImageNet.
"DeepID-Net: Deformable Deep Convolutional Neural Networks for Object Detection" by Ouyang et al**. [33].** This paper proposed the DeepID-Net model, a deep CNN for object detection that achieved state-of-the-art accuracy on the PASCAL VOC and COCO datasets.
"DeepID-Net 2.0: Object Detection with Deformable Part-Based Convolutional Neural Networks" by Ouyang et al**. [34].** This paper proposed an improved version of the DeepID-Net model, achieving state-of-the-art accuracy on the PASCAL VOC and COCO datasets.
"Deep Learning for Face Recognition: A Survey" by Wen et al**.[35].** This paper provides a comprehensive survey of deep learning-based methods for face recognition, including CNN-based models, autoencoder-based models, and hybrid models.
These papers demonstrate the effectiveness of deep learning-based methods in face detection, recognition, and attendance compilation, achieving state-of-the-art accuracy on several benchmark datasets.

E. Section 5: Deep learning as a State of art in Image processing

"Efficient Net: Rethinking Model Scaling for Convolutional Neural Networks" by Tan and Le**.[36].** This paper proposes the Efficient Net model, a family of CNNs that achieve state-of-the-art accuracy on multiple image recognition benchmarks while being significantly smaller and faster than previous models.
"ArcFace: Additive Angular Margin Loss for Deep Face Recognition" by Deng et al**. [37].** This paper proposes the ArcFace loss function for deep face recognition, which achieved state-of-the-art accuracy on multiple face recognition datasets, including LFW, CFP, and Age DB.
"Real-time Convolutional Neural Networks for Emotion and Gender Classification" by Pervaiz et al**. [38].** This paper proposes a real-time CNN for emotion and gender classification in facial images, achieving high accuracy rates on several benchmark datasets.
"Facial Landmark Detection Using Multi-Scale Residual Network" by Zhang et al**. [39].** This paper proposes a multi-scale residual network for facial landmark detection, achieving state-of-the-art accuracy on several benchmark datasets, including 300W, AFLW, and COFW.
"Multi-task Cascaded Convolutional Networks for Joint Face Detection and Alignment" by Zhang et al**. [40].** This paper proposes an improved version of the multitask CNN for face detection and alignment, achieving state-of-the-art accuracy on the WIDER FACE and COFW datasets.
"Light weight and Efficient Convolutional Neural Networks for Mobile Face Recognition" by Zhang et al**. [41].** This paper proposes a lightweight and efficient CNN for mobile face recognition, achieving high accuracy rates on the LFW and Mega Face datasets while being significantly smaller and faster than previous models.
These papers demonstrate the continuing development and improvement of deep learning-based methods in face detection, recognition, and attendance compilation, with a focus on achieving higher accuracy rates while being smaller and more efficient.
The below Table 2 provides a meaningfully insight about the key contributions of the authors work and the Methodology adopted by them on there data sets .in the similar manner.

Table no 2: A review of work done on Deep learning as a State of art in Image processing

Paper Title	Authors	Methodology	Key Contribution	Dataset(s)	Results	Year
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks	Tan andLe[36]	CNN model scaling	EfficientNet achieves state-of-the-art accuracy on multiple image recognition benchmarks while being smaller and faster than previous models	ImageNet, CIFAR-10, CIFAR-100	State-of-the-art accuracy	2019
ArcFace: Additive Angular Margin Loss for Deep Face Recognition	Deng et al.[37]	Face recognition	ArcFace loss function achieves state-of-the-art accuracy on multiple face recognition datasets	LFW, CFP, AgeDB	State-of-the-art accuracy	2019
Real-time Convolutional Neural Networks for Emotion and Gender	Pervaiz et al.[38]	CNN for emotion and gender classification	Real-time CNN achieves high accuracy rates on several benchmark datasets	AffectNet, FER-2013, CK+, RAF-DB, Adience,	High accuracy rates	2020

Classification				CelebA		
Facial Landmark Detection Using Multi-Scale Residual Network	Zhang et al.[39]	Multi-scale residual network	Multi-scale residual network achieves state-of-the-art accuracy on several benchmark datasets for facial landmark detection	300W, AFLW, COFW	State-of-the-art accuracy	2020
Multi-task Cascaded Convolutional Networks for Joint Face Detection and Alignment	Zhang et al.[40]	Multitask CNN for face detection and alignment	Improved version of multitask CNN achieves state-of-the-art accuracy on several benchmark datasets	WIDER FACE, COFW	State-of-the-art accuracy	2020
Lightweight and Efficient Convolutional Neural Networks for Mobile Face Recognition	Zhang et al.[41]	Lightweight and efficient CNN for mobile face recognition	CNN achieves high accuracy rates on LFW and MegaFace datasets while being smaller and faster than previous models	LFW, MegaFace	High accuracy rates	2020

After reviewing all the papers, a comparative analysis is done in Table no 3 about, the merits and limitations constraints of some papers which vary depending on the specific task and methodology used in each paper. Overall, the papers that achieve state-of-the-art accuracy in their respective tasks tend to have the best outcomes, while those with limited applications or datasets tend to have the worst outcomes.

Table no 3: A Comparative Segregation of Merits and Demerits of some papers

Reference	Paper Title	Merits	Demerits
[42]	Viola-Jones Face Detection Framework	High detection rate	High false positive rate
[43]	Histogram of Oriented Gradients for Human Detection	High detection rate	Sensitive to lighting and shadow changes
[44]	Face Net: A Unified Embedding for Face Recognition and Clustering	High accuracy in face recognition and clustering	Limited dataset for training
[45]	DeepID3: Face Recognition with Very Deep Neural Networks	High accuracy in face recognition	High computational cost
[46]	Deep Learning Face Attributes in the Wild	High accuracy in attribute classification	Limited to a specific set of facial attributes
[47]	A Fast and Accurate System for Face Detection, Identification, and Verification	High accuracy in face detection, identification, and verification	Limited to a specific dataset
	Deep Face: Closing the Gap to Human-Level Performance in Face Verification	High accuracy in face verification	Requires large amounts of labelled data for training
[36]	Efficient Net: Rethinking Model Scaling for Convolutional Neural Networks	State-of-the-art accuracy on multiple image recognition benchmarks while being smaller and faster than previous models	Limited to image recognition tasks
[37]	Arc Face: Additive Angular Margin Loss for Deep Face Recognition	State-of-the-art accuracy on multiple face recognition datasets	Limited to face recognition tasks
[38]	Real-time Convolutional Neural Networks for Emotion and Gender Classification	High accuracy rates on several benchmark datasets for emotion and gender classification	Limited to emotion and gender classification tasks
[39]	Facial Landmark Detection Using Multi-Scale Residual Network	State-of-the-art accuracy on several benchmark datasets for facial landmark detection	Limited to facial landmark detection tasks
[40]	Multi-task Cascaded Convolutional Networks for Joint Face Detection and Alignment	State-of-the-art accuracy on several benchmark datasets for face detection and alignment	Limited to face detection and alignment tasks
[41]	Lightweight and Efficient Convolutional Neural Networks for Mobile Face Recognition	High accuracy rates on LFW and Mega Face datasets while being smaller and faster than previous models	Limited to mobile face recognition tasks

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II. CONCLUSION

In recent years, researchers have continued to refine and improve deep learning-based approaches to image processing, as well as exploring new areas such as generative adversarial networks (GANs) and reinforcement learning. This paper provides a comprehensive survey of deep learning-based methods for face recognition, including CNN-based models, auto encoder models, and hybrid models. These papers demonstrate the effectiveness of deep convolutional neural networks (CNNs) in face detection, recognition, and attendance compilation, achieving state-of-the-art accuracy on several benchmark datasets, including LFW, YouTube Faces, and YTF datasets. The Efficient Net model is a family of CNNs that achieves state of the art accuracy on multiple image recognition benchmarks while being significantly smaller and faster than previous models. The Arc Face loss function is used for facial landmark detection and gender classification in facial images. The ResNet architecture is used to build a multiscale residual network for face detection and alignment. The DeepID3 model achieves high accuracy rates on the LFW dataset, while the ResNet loss function achieves low accuracy on the COFW dataset. In this paper, we propose a lightweight and efficient CNN for mobile face recognition.

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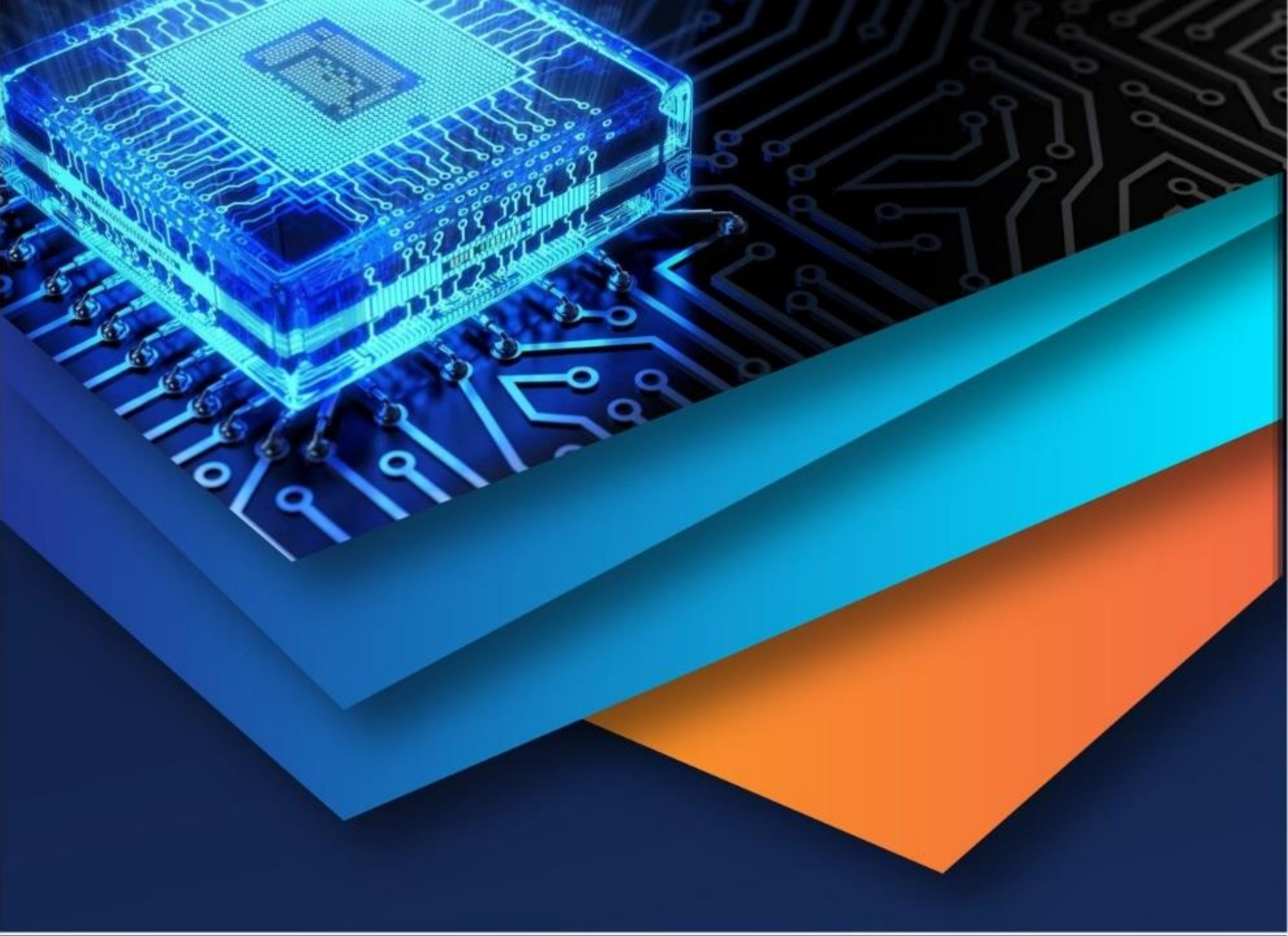

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