



Face Detection Technique Using Convolutional Neural Networks (CNNs) and MobileNet

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ABSTRACT

Facial detection has become a significant advantage in the field of image forensic and computer vision. These provide help in detecting an image that are doctored in order to hide or conceal information/message. Researchers used extensive deep learning applications particularly those algorithms that highlight potential for detecting facial recognition to address issues such as high computation, long operation time and low accuracy in traditional and lightweight face recognition algorithms, we introduce a face recognition method that incorporates a lightweight neural network and multi-hash recognition degree weighting. Firstly, the front-end feature extraction in the SSD detection network utilizes the improved MobileNet model instead of the VGG model. The pruned SSD model is employed as the detection network, reducing calculation time and preventing overfitting. Secondly, face matching involves weighing the calculated mean hash similarity and perceived hash similarity using a specific weight. The proposed improved method is trained and evaluated on WiderFace, LFW and FDDB datasets. Experimental results demonstrate that the method enhances running speed by approximately 29% on LFW datasets while achieving a high face recognition rate and maintaining detection performance. This research introduces a novel and high-performance approach to the field of face recognition.

Keywords: Digital Forensics, Image Forgery, Convolutional neural networks (CNNs), MobileNet, Python and OpenCv.

1.0 INTRODUCTION

Face is one of the most important biometric features of a human. A human can recognize different faces without difficulty. Yet, it is a challenging task to design a robust computer system for face identification. The inadequacy of automated face recognition systems is especially apparent when compared to our own innate face recognition ability (Arnold et al., 2019; Roulshen, et al., 2020). Human perform face recognition, an extremely complex visual task, almost instantaneously and our own recognition ability is far more robust than any computer can be. In a bid to make computer recognizes faces, the technology of face recognition was introduced since the early 1960s (Chun et al., 2024). Face recognition is one of the most important applications of biometrics-based authentication system which uses a computer to automatically identify and analyse facial visual features (Anas et al., 2023).

It belongs to the category of computer vision and the field of artificial intelligence such as deep learning and pattern recognition. Face recognition refers to biometrics recognition task, where a face is categorized as either known or unknown after comparing it with the images of a known identity stored in the database (Zhalgas, Amirgaliyev, & Sovet, 2025). Face recognition is a challenge given the certain variability in information because of random variation across different people, including systematic variations from

various factors such as lightening conditions and pose (Lu et al., 2025; Nandini, et al., 2020). The technology face recognition is identified as an active area of research in recent years because of the rise in security demands and the potential of the technology in law enforcement and commercial use (Jain & Li, 2021). Face Recognition contains two operational modes. First, verification mode is known as one-to-one matching in biometrics. The verification operational mode is used to pick out a face out of many faces in a face database to find out whether the face details belong to a particular person. Second, the identification mode is known as one-to-many matching. Identification involves taking the individual and comparing their biometrics to a database of possible identities. Face recognition technology consists of four stages, which include face detection, alignment, representation (facial feature extraction), and classification (Prasad et al., 2019).

Computational methods of face recognition need to address numerous challenges. These types of difficulties appear because faces need to be represented in such a way that best utilizes the available face information to define a specific face from all the other faces in the database. Face pose is a specifically difficult problem in this aspect simply because all faces seem similar; specifically, all faces consist of two eyes, mouth, nose, and other features that are in the same location (Hu et al., 2019). The technology of Face

Recognition is widely used in public security, daily life, military areas, banks as an access control method for identifying a particular individual. Face recognition is one of the major applications of computer vision. A facial recognition system is a technology capable of matching a human face from a digital image or video frame against a database of faces (Dewi & Septadepi, 2020). Typically employed to authenticate users through identity verification services. With the development of deep learning, face recognition technology based on CNN (Convolutional Neural Networks) has become main method adopted in the field of face recognition such access control security, attendance, candidate identification, character recognition, face payment and other fields (Jing et al., 2019). A convolutional neural network (CNN) is type of artificial neural network that has one or more convolution layers and are used mainly for image processing, classification, segmentation and also for other correlated data (Pranav & Manikandan 2020).

In order to detect faces, Convolutional neural networks have been studied since the 1980s (Aneesa et al., 2022). Because of the research significance and bright application, prospect of face recognition technology, more and more organizations have begun to study it, including Universities like Massachusetts University of Technology, Stanford University, Perking University, Harbin Institute of technology and many others (Chen & Wang, 2022). Today's face recognition field has made a lot of progress, making the technology in both detection speed and recognition accuracy greatly improved (Ruishen et al., 2022).

Deep learning is a machine learning based artificial neural networks that recognize patterns by progressively extracting features from data through higher layers (Wang et al., 2020). The benefit of using Convolutional Neural Networks is their ability to develop an internal representation of two dimensional-images that allows model to learn position and scale of faces in an image (Chen & Wang, 2022). With the development of convolutional neural networks, the achievements made in various competitions are getting better and better, making it the focus of research (Jing et al., 2019). With the development of Convolutional neural networks in recent years, the application of deep learning on face recognition can express the original face information more essentially, and the accuracy rate of the face recognition has been rapidly improved through the feature extraction and autonomous learning of network deep learning (Sun et al., 2022). Convolutional Neural Networks are reliable, accurate and used to minimize data pre-processing. In this paper, we are using OpenCv open-source library for image pre-processing tasks such as face detection, face alignment and cropping. On the other hand, we used the CNN for extracting features from the images, training, testing and evaluating the face recognition

model.

1.1 Representation of Image in a Computer

An image is made up of sample points of pixels. The image generated by capturing a real scene through a device is stored in a bitmap after been digitalized inside the computer (Pranav et al., 2020). An image composed of M rows and N columns of sample pixels. Each pixel is a small square that represents a single point in the image. The colour and intensity of each pixel determines the appearance of an image. For a colour image, each pixel is typically composed of three channels Red Green and Blue (RGB). The combination of intensities in these channels determines the overall colour of the pixel. The number of pixels in an image determines its resolution.

2.0 REVIEW OF RELATED LITERATURE

Face detection is a diverse research area in image forgery and computer vision with numerous applications ranging from biometric authentication, identity verification to surveillance system. (Guosheng et al., 2018). Over the years, Convolutional Neural Networks was regarded as a powerful approach for face recognition, outperforming the normal and traditional approaches and providing efficient and effective service.

Facebook AI Research group (Yahia, Mohammad, & Hossam, 2020) developed a robust CNN-Based face recognition model termed DeepFace, which was trained on a dataset of diverse collection of photos from Facebook referred to as Social Face Classification (SFC). The architecture of the DeepFace constitutes of nine-layer neural networks with over 120 connection weight, extracts low-level-features and making the output more robust to local translations.

Normally in the traditional ways, images are aligned in 2D before they are fed into the CNN model which cannot handle out-of-plane rotation, in order to outcome this limitation, the DeepFace come up with a 3D alignment method using an affine camera model (Xion, et al., 2020). In addition to DeepFace, another notable CNN model for face recognition is DeepID, proposed by (Yahia, Mohammad, & Hossam (2020) researchers at the Chinese University of Hong Kong as one of the Convolutional Neural Networks models for Face Recognition named DeepID. DeepID was trained on a large dataset of faces image collected from the web called CASIA-Webface, it contains over 400,000 face images of over 10,000 different individuals. The model of DeepID is set to learn features by training on ensemble of small CNNs used for network fusion, unlike other models like the DeepFace whose features are learned by one single big CNN, in DeepID, the input of one single CNN is the crops/patches of facial images and the features learned by the CNNs are concatenated and gathered together to form a powerful

feature.

To address the gap of overfitting data variability, (Yahia, Mohammad, & Hossam (2020) make use of the CASIA-Webface. The CASIA-Webface dataset of the DeepID was collected in a variation of environmental conditions, including different poses, lightening conditions, various facial expressions and other environmental conditions. This helped to enhance robustness and efficiency on CNN model and to achieve state-of-the-art results in face recognition. Further researches were proposed to improve the effectiveness and performance of DeepID; such as DeepID2, DeepID2+ and DeepID3 (Liao et al., 2022). DeepID2 is an extensive and advance work on the DeepID, which trains the CNN for Verification and identification. The Advancement of both DeepID and the DeepID2 is the DeepID2+ (Sun et al., 2022). proposed to enhance the performance of both DeepID and the DeepID2, which extends the DeepID2 by: Additional branches of the network providing 20 layers including ten 10 convolutional layer and ten 10 fully connected layers, Additional number of filters to all layers and Training on larger dataset.

As the field of computer vision is getting significant improvement, more and more topics were proposed in the field of face recognition. (Wei et al., 2023) used the deep learning approach for identification of specific individual in animals, which they split into two

formulations: a deep pre-trained convolutional neural network model and a self-convolutional network. Dyeni, (2025) proposed another face recognition pipeline, known as the WebFace, which derives its face representations on using the convolutional neural networks (CNN). The web face architecture is composed of 17 layers which includes ten 10 Convolutional layers which are followed by a 3 x 3 filters, five 5 pooling layers and 2 fully connected layers.

The data base used for Webfaces is a large dataset of different subjects of around 10,000 with 500,000 faces. Yahia et al., (2020) in their work titled "Design of a Face Recognition System based on Convolutional Neural Network (CNN)" reported to have a training accuracy 99.78% and a validation accuracy of 98.7%, by using a CNN model of two 2 convolutional neural layer and a single fully connected layer. After defining the loss function and the optimization algorithm, the CNN was trained on the ORL dataset for 20 epochs, with 400 iterations in each epoch. The loss function reaches a minimum value of 0.12 on the testing set (validation). To show increase in the diversity of training data (Guosheng et al., 2018) make use of various Data augmentation techniques such as rotation, brightness adjustment and horizontal / vertical flips to provide better generalization of the CNN model on an unseen data.

Table 2.1 Summary of the related works

Authors & year.	Convolutional (CNN) Model	Dataset	Accuracy
Yahia, Mohammad, & Hossam, (2020)	DeepFace based on	Labelled Face in Wild (LFW) dataset, SFC and YTF	97.53%
Yi, et al., (2021)	DeepID	YTF, CASIA-Webface and Labelled Face in Wild (LFW)	97.35%
Sun, et al., (2022)	DeepID2+	YTF, CASIA-Webface and Labelled Face in Wild (LFW)	99.47% (LFW)
Yahia et al., (2020)	CNN	ORL	93.2% (YTF)
Dyeni et al., (2025)	WebFace	Self-collected Dataset	99.78%
Guosheng et al., (2018)	CNN, DNN	YLF, LFW	93.56%
			95.02%

2.1 Review of Related System

In the convolution neural networks, face representation extensively affects the performance of the face recognition system and has also become a focus of attention in the current face recognition research. Various CNN architectures have been proposed for the face recognition varying in terms of strengths and limitations. Here in this section, we highlight some known convolutional neural networks that are often used in the various field of the computer

vision including the face recognitions system, handwritten digit detection and many more.

- i. AlexNet: The work of (Krizhevsky et al., 2022) introduced the AlexNet as a convolutional neural architecture with five (5) convolution layers, three (3) max pooling layers and three 3 fully connected layers and uses the rectified linear units (ReLU) as the activation function which provides faster training than the traditional activation function like sigmoid and

tanh. The AlexNet demonstrated the potential of CNNs in various image classification tasks and happen to be the first CNN to achieve a ground-breaking result in the ImageNet Large-Scale Visual Representation Challenge in 2022, with a top 5 error of 16.4%.

- ii. ResNet: (Volker et al., 2023) developed the ResNet of deep residual networks. This is one of the networks that are considered the latest and greatest in terms of using convolutional neural networks for image recognition. ResNet also won the ImageNet Large-Scale Visual Recognition Challenge in 2023 (ILSVRC-25) with a top 5 error of 3.57%. It includes five convolutional layers

ResNet-50 architecture uses a [224 x 224 x 3] image as an input.

- iii. VGGNet: The VGGNet known as the Visual Geometry Group Network is another CNN architecture introduced by (Simonyan & Andrew, 2024). University of Oxford in a paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition". The VGGNet architecture consist of 16 to 19 convolutional layers with very small 3 x 3 convolutional filters throughout all the network, followed by a max pooling layer with a 2 x 2 filter and 2 strides, and several fully connected layers

Table 2.2 Details of CNN Architectures

Architecture	Year	Depth	Convolution filters	pooling layers	Fully connected Layer
VGGNet	2024	16 – 19 layers	Consists of 3 x 3 filters throughout	2 x 2 max pooling after every 2 or 3 CNN layers	No fully connected layer
ResNet	2023	Varies up to hundreds (eg. ResNet-50, ResNet-101)	Different filters of 3 x 3 and 1 x 1 filters	2 x 2 max pooling with strides 2 in initial layers	No fully connected layer on the original design
AlexNet	2022	8 layers	11 x 11, 5 x 5, and 3 x 3	2 x 2 max pooling after every 2 CNN layers	3 fully connected layers

2.2 Datasets for Training and Evaluation of CNN model

Selection of good and appropriate dataset for training and evaluation of CNN model is another crucial aspect that affect CNN model. There are several face databases are available to face recognition researchers. These databases are different in size, scope, and purpose. The photographs in many of these databases are acquired by small research teams specifically to study face recognition.

- i. The CASIA-Webface (Wang 2020): is face recognition dataset collected from the internet which contains over 400,000 face images of over 10,000 different individuals. In a variation of environmental conditions, including different poses, lightening conditions, and

other environmental conditions. This helped to enhance robustness and efficiency on the CNNs model and achieve state-of-the-art results in face recognition. The CASIA-Webface is commonly used in various CNN models such as the DeepID, DeepID2 and the DeepID2+.

- ii. The YouTube face (YTF) (Wile et al., 2019). The dataset contains 3425 videos collected from YouTube. The videos are a subset of the celebrities in the LFW. The videos contain 1595 individuals. In our study, we used images taken from video.

- iii. Labelled faces in the wild (LFW) (Huang et al., 2020): This dataset is a benchmark dataset designed for studying the problem of unconstrained face recognition. The dataset contains more than 13,000 images of faces collected from the web. Each face has

been labelled with the name of the person pictured. A total of 1680 of the people pictured have two or more distinct photos in the database.

- iv. ORL (Drozdzowski et al., 2021): this is database utilized in recognition experiments. It contains 10 unique images of 40 individuals, adding up to a total of 400 images that have different face angles, facial expressions, and face details. The dataset has a collection at the Olivetti Research Laboratory at Cambridge for some individuals.
- v. Georgia Tech face database (Nefian, 2022): This database contains sets of images for 50 individuals, and there are 15 colour pictures for each person. Most of the pictures were taken in two different sessions to consider the variations in illumination conditions, appearance, and facial expression. Also, the images in the datasets were taken at different orientations and scales.

3. 0 METHODOLOGY

The dataset we utilized throughout the training and evaluation of the model was LFW dataset. The LFW dataset is widely used as a benchmark in the field of face recognition. It comprises 5,749 images, each tagged with a name and a distinct identifier, totaling 13,233 faces. These images showcase celebrities sourced from the internet. This dataset presents a diverse collection of facial images, making it a valuable resource for evaluating the performance of

face recognition algorithms. The WIDER Face dataset stands as another widely used resource for face detection and recognition. It encompasses 393,703 annotated face images within a total of 32,203 images. This dataset incorporates a range of environmental variables such as occlusion, blurring, and multi-scale factors. Additionally, it features 61 intricate scenes, introducing even more demanding scenarios for face annotation and assessment. The WIDER Face dataset is acclaimed for its large-scale and intricate scenes, making it well-suited for the evaluation of face detection algorithms. Figure 2 in the paper provides a partial glimpse into the WIDER Face dataset, offering insight into its intricate and diverse nature. The Fddb dataset is specially curated for face detection tasks, featuring images captured in natural settings with diverse face poses, resolutions, shadows, and varying degrees of focus. It encompasses both color and grayscale images, totaling 2,845 face images with 5,171 labeled face regions. The face regions in the Fddb dataset are annotated with precise face coordinates and labels. Serving as a comprehensive benchmark, the Fddb dataset is invaluable for evaluating face detection algorithms. Figure 3 in the scheme showcases a selection from the Fddb dataset, highlighting the range of face poses and conditions captured within the dataset.



Figure 2. WIDER Face data set sample example



Figure 3. Fddb data set sample example

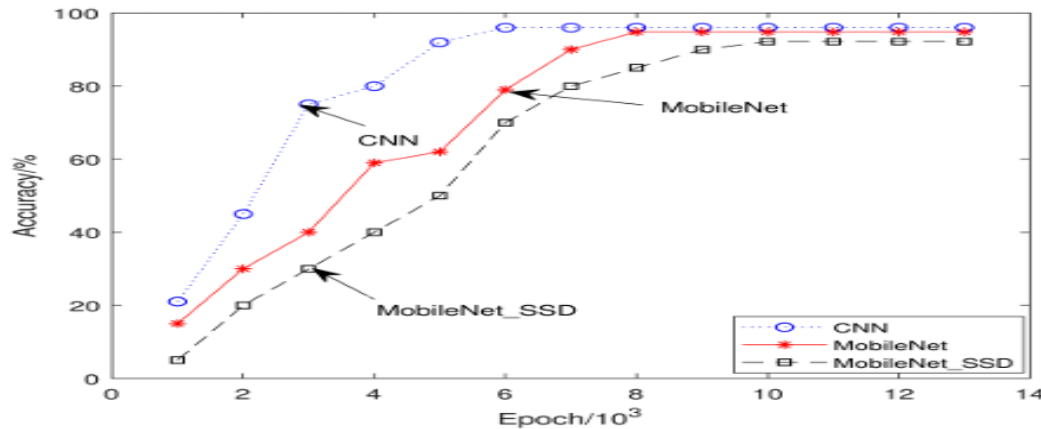


Figure 4. Comparison of accuracy of the three models. The figure illustrates the accuracy trend of the three models on the LFW data set as the number of iterations increases.

4.0 RESULT

A. Experimental setup

The experiments detailed in this scheme were conducted on an Ubuntu system, which served as the operating platform for executing the tests and performing the assessments. Regarding the network training parameter configurations, the learning policy is customized to meet the experiment's specific requirements. More precisely, the initial learning rate is set at 0.001, determining the size of steps taken by the model to adjust its internal parameters during training. Additionally, the weight decay is set to 0.0004, controlling the level of regularization applied to the network's weights to guard against overfitting.

The proposed scheme performance is evaluated using Convolutional Neural Networks (CNN) and MobileNet architectures. These architectural choices are highly regarded in the realm of computer vision tasks, particularly in tasks such as face detection and recognition, due to their effectiveness in extracting significant features from images.

The assessment is conducted on three established benchmark datasets: LFW (Labeled Faces in the Wild) (Tabaie *et al.*, 2022), WIDER Face (Ismail *et al.*, 2019) and FDDB (Face Detection Data Set and Benchmark) (Feng *et al.*, 2019). These datasets hold significant recognition in both face detection and face recognition domains, providing standardized metrics for evaluating various algorithms and methodologies. By subjecting the proposed method to tests on these datasets, researchers can assess its precision,

resilience, and ability to generalize across different scenarios.

B. Performance evaluation

In this scheme, Figure 4 presents a comparative analysis of the accuracy between MobileNet SSD, CNN (Jiangyu *et al.*, 2019) and MobileNet using the LFW dataset. The graph illustrates how the accuracy of each model evolves with increasing iterations during the training process. It is evident from the graph that as the number of iterations grows, all three models tend to reach a point of convergence. Among these methods, CNN achieves the earliest convergence, attaining a consistent accuracy of 96% between 4,000 and 5,000 iterations. The highest accuracy rate among the three methods, once stabilized, belongs to CNN. MobileNet SSD and the enhanced MobileNet method take approximately 8,000 and 10,000 iterations, respectively, to converge. The enhanced method achieves a convergence accuracy of around 94.8%, while the accuracy of the improved MobileNet model is 92.2% upon convergence. These findings indicate the viability of the proposed approach, demonstrating promising results. In contrast to the conventional CNN approach, both MobileNet SSD and the adapted MobileNet method exhibit a decline in accuracy. Nonetheless, MobileNet SSD holds an edge in computational speed and reduced network parameters. While the accuracy of the MobileNet SSD model surpasses that of the adapted MobileNet model by two percentage points, it doesn't reach the level of the traditional CNN method.

Table I. Comparison was made between the three models in terms of the number of parameters and recognition accuracy on the LFW data set.

Network structure	Parameter quantity	Accuracy
CNN	25000000	96%
MobileNet	3600000	92.2%
MobileNet SSD	3000000	94.8%

Table II: Comparison of running speed between the two models. (MS)

Model	Min	Max	Avg
MobileNet	136.31	147.63	141.97
MobileNet SSD	106.63	119.24	112.93



Figure 5. Face detection results on the WIDER Face data set.



Figure 6. Face detection results on the Fddb data set.

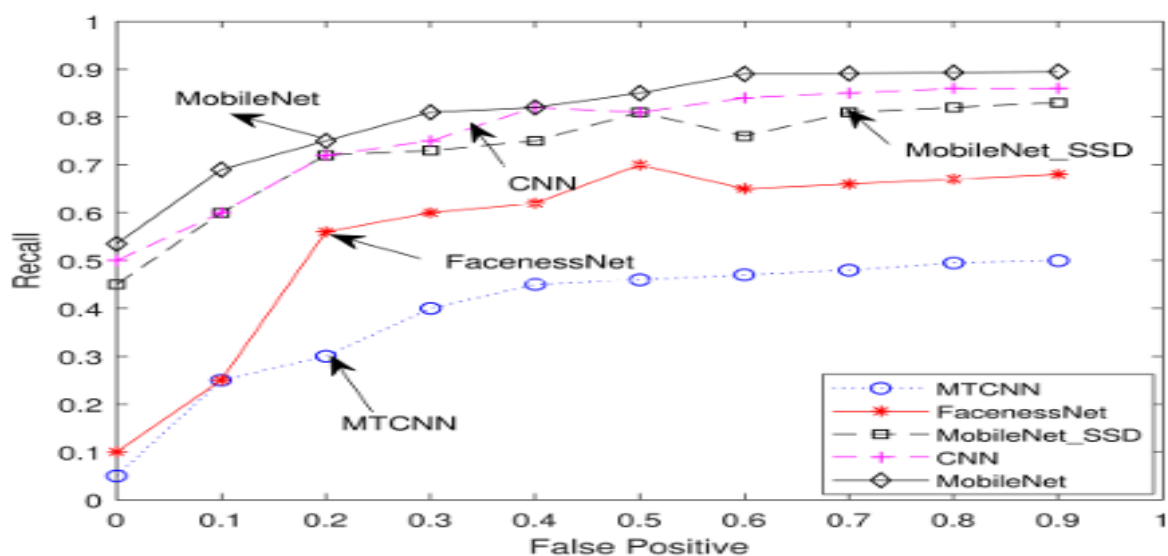


Figure 7. ROC curve comparison diagram. The figure illustrates the test performance of the proposed model and a comparison method on the FDDb data set.

with a higher value (closer to 1) denoting superior detection accuracy and resilience. From the graph, it is evident that our proposed model achieves a TPR of over 92% on the FDDB dataset, demonstrating suitability for various real-world scenarios. Upon comparing the methods based on ROC curves, it is apparent that the MobileNet method exhibits a narrower feature distribution and weaker randomness compared to the other approaches. Nonetheless, our proposed MobileNet SSD displays a reasonably moderate AUC value, indicating its proficiency in accurately distinguishing face regions from non-face regions. In terms of TPR, our proposed MobileNet SSD achieves an approximate value of 0.535 at an FPR of 0. This further underscores the high detection accuracy of our proposed method. While its AUC value may not be the highest among all methods, it surpasses that of the modified MobileNet algorithm.

5.0 CONCLUSION

We introduce a face recognition method that leverages lightweight neural networks and the dohadic weighting technique. Our approach incorporates pruned SSD with a weighted mean hash similarity value and perceptual hash similarity value in the detection network. Through multiple experiments, we demonstrate that the proposed method achieves an average face recognition accuracy of approximately 95% and an average recognition time of about 112ms. However, our proposed scheme has some limitations, particularly when dealing with low-definition images, as they can lead to reduced recognition performance. In future, work should focus on optimizing the proposed model to address this challenge and further improve the overall face recognition rate.

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