This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3187686

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier XXX/XXX

iFace 1.1: A Proof-of-Concept of a Facial Authentication Based Digital ID for Smart Cities

ALAKANANDA MITRA[1], (Graduate Student Member, IEEE), DAN BIGIOI[2], SARAJU P. MOHANTY[1], (Senior Member, IEEE), PETER CORCORAN[2], (Fellow, IEEE), and ELIAS KOUGIANOS[3], (Senior Member, IEEE)

[1]Dept. of Computer Science and Engineering, University of North Texas, USA
[2]College of Science and Engineering, (C3I Research Centre), National University of Ireland, Galway, Ireland, (email: d.bigioi1@nuigalway.ie)
[3]Dept. of Electrical Engineering, University of North Texas, USA

Corresponding author: Dan Bigioi (e-mail: d.bigioi1@nuigalway.ie).

ABSTRACT "Smart Cities" are a viable option to various issues caused by accelerated urban growth. To make smart cities a reality, smart citizens need to be connected to the "Smart City" through a digital ID. A digital ID allows citizens to make easy and effective use of amenities provided by the smart city such as healthcare, transport, finance, and energy. In this paper, we propose a proof-of-concept of facial authentication based end-to-end digital ID system for a smart city. Facial authentication systems are prone to various biometric template attacks and cyber security attacks. Our proposed system is designed to detect the first type of attack especially deepfake and presentation attacks. Users are authenticated each time before using facilities in the smart city. Authentication is performed on edge devices, making the process more secure as no data leaves the device during authentication. Facial data is stored at the cloud in a look up table format with an unidentifiable username. Our proposed solution achieved 97% accuracy in authentication with a False Rejection Ratio of 2% and False Acceptance Ratio of 3%.

INDEX TERMS Smart City, Digital ID, Internet-of-Things (IoT), Deepfake, Presentation Attack, Facial Authentication System, Convolutional Neural Network, Triplet Loss, Look Up Table

I. INTRODUCTION

The world's population is increasing at an unprecedented rate. It is estimated that 70% of the global population will be living in cities by the year 2050 [1]. Such rapid urbanization will create more carbon emissions and pollution which in turn will negatively impact the environment and people's health. It will also create a greater demand for energy, food, and resources. Smart cities have emerged as a resilient and sustainable solution to the problems caused by rapid urbanization. They are envisioned as the future of urbanisation, where residents of such cities can benefit from smart transportation, health care, energy, and other seamlessly integrated services which are all connected through the Internet of Things (IoT). Fig. 1 shows how smart city stakeholders are connected.

In the last twenty years, the idea of a smart city has stepped forward due to advancements in hardware and software technologies, growth in information and communication technologies (ICT), and initiatives offered by various tech giants [2].

For a practical implementation of the smart-city digital infrastructure, citizens should have a way to easily connect to the amenities offered by the smart city. They should be able to benefit from the various services offered such as smart healthcare, government, and financial services among others. It is interesting to note that people have already started to transform traditional cities into "smart cities" through actions such as checking their bank accounts using apps, purchasing items online, using smartphones, driving electric vehicles, locking doors with smart locks, lighting homes with smart lights, paying at electronic parking meters, disposing trash in smart bins, etc. Therefore, in this paper we propose that a universal digital identity system can unlock the full potential of a smart city, by connecting the citizen to all of its amenities in a simple and efficient manner.

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3187686

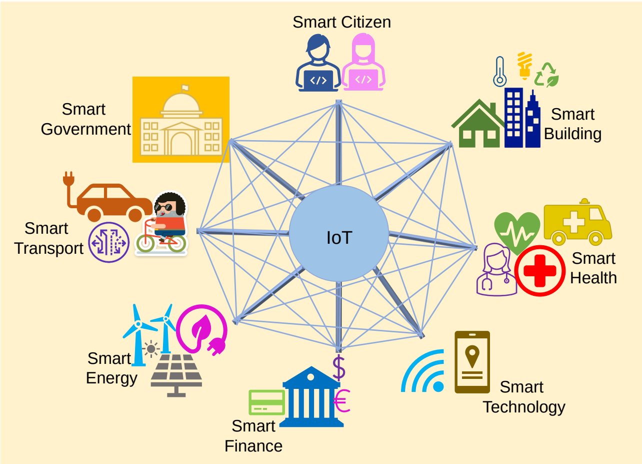


FIGURE 1. Components of Smart City

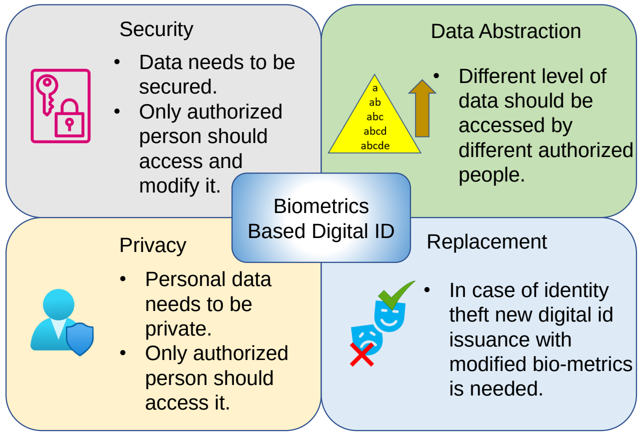


FIGURE 2. Mandatory Requirements for Digital ID in a Smart City.

The use of digital IDs has already started to become the norm in various parts around the world e.g., India's *Aadhaar*, a biometric based id number, the digital ID system in Australia, and the digital ID wallet initiative in the EU. The use of a digital ID for smart cities explores a similar concept, adding additional safeguards to protect against biometric Deep Fake attacks.

In this paper, we propose a proof-of-concept facial authentication based digital ID system to allow citizens to easily avail of the facilities provided by smart cities. The proposed system shows a high success rate in detecting presentation and Deep Fake attacks. Our goal is to provide the digital identification infrastructure necessary for citizens to access the various facilities provided by smart cities in an easy and effective manner. This paper was originally presented in [3].

The rest of this paper has been organised following: Section II presents a detailed discussion on digital ID and smart cities, the need of a digital ID in a smart city, and the challenges of implementing the digital ID system. Section. III discusses the novel contributions of our work. Related works are discussed in Section IV in a smart city context. Section V depicts the proposed work. Performance of the face authentication system is presented in Section VI. Section VII winds up the paper with suggestions for future work.

II. DIGITAL ID AND SMART CITY

A. ROLE OF DIGITAL ID IN SMART CITY

In traditional cryptographic systems secret keys are used to authenticate users. Often-times users write down their secret keys, save them somewhere, share them with others, or simply forget them. Sometimes the keys are so simple or tied up with peoples' life events that they are easy to predict. If the secret key is no longer private, the authentication system collapses.

On the other hand, biometrics based digital IDs are person-dependent and discrete as bio-metrics represent physiological or behavioural traits of a person. With such an ID, there is no need to preserve the confidentiality of the key, because the users themselves are the secret keys. Activities such as opening a bank account or availing of any age restricted service require proper user verification. A digital ID can reduce the paperwork typically associated with such activities, giving citizens easy and efficient access to all services provided by the smart city. The importance of using a digital ID in a smart city is multi-fold:

1) Digital ID system revamps the operational capacity of a city at a granular level.
2) Emergency medical services will be improved by introducing digital ID. If a critically sick person reaches a hospital without any traditional ID, a digital ID can save their life. The doctor can access the patient's medical history and give proper medical care.
3) During any natural disasters, efficient verification of individuals identities can be performed.
4) Digital ID's can facilitate improved administrative capacity for amenities around smart cities, eg banks, drivers licenses, retail, and transportation.
5) Online education is operating in parallel with the traditional brick and mortar schooling system. A Digital ID will offer more flexibility to both students and educators.

B. CHALLENGES OF DIGITAL IDENTIFICATION

Building such a system is challenging in the context of various concerns such as cyber security attacks, data privacy, security, and inclusivity.

1) Vulnerability to Biometrics and Cyber Security Attacks

Biometric based digital ID systems are prone to various biometric and cyber security attacks. As our proposed digital ID is facial biometric based, biometric attacks are our area of concern.

a: Presentation Attack

The proposed digital ID verification system is reliant on accurate face recognition. Facial Recognition software is vulnerable to face spoofing or presentation attacks. The vulnerable points of a digital identity system (DIS) are listed in Table. 1 [4]. The first two attacks of the table are a presentation attack.

b: Deepfake Attack

Another common vulnerability is a Deep Fake attack. Deep Fakes are AI generated fake images/videos which do not exist and deceive human eyes easily. It is a type of presentation attack [5]. It also poses serious threat to facial recognition systems [6]. With the rapid progress of deep learning, Deep Fakes are gaining the potential to fool even the best facial recognition systems.

Face swapping through Face Swapping Generative Adversarial Network (FSGAN) [7] eases the creation of deep fakes as there is no need to train the FSGAN for hours with source and target images. It means Deep Fakes can spread more quickly and easily than ever before as people with a basic knowledge of this technology are now capable of creating them.

c: Indirect Attack

In Table. 1 attacks from $3-8$ are indirect attacks. These attacks target the cyber security system directly, rather than biometric attack, as they target databases, or channels, or even the device itself. In this paper, indirect attacks have not been addressed as they fall outside the scope of this work.

2) Privacy and Data Security

Fig. 2 depicts the conditions of a bio-metric based digital ID. Two major concerns are the security and privacy of information. Data should be secured and obtained only by the entitled person. Data abstraction should also be followed where people with different levels of authorization should be able to access different levels of data. As digital ID is related to someone's biometric data, storing this data safely is another important factor. So, the design approach needs to be secure-and-private-by-design [8].

3) Exclusion

Ideally, everyone in the smart city should be enrolled in the digital ID system. However, there will be scenarios e.g., people may not want to be enrolled in the system, people may not be capable of providing the required biometrics due to physical disabilities, or they may not be digitally aware. In those scenarios, alternative traditional identification e.g., paper ID is required.

4) Data Privacy Regulation Policy

Data privacy regulation policies are different across the globe. Europe has the consumer General Data Protection Regulation (GDPR) whereas North America has different regulations like HIPAA, FERPA, COPPA, and FCRA for different types of data. There are many more such regulations worldwide and any physical digital ID system for a city would have to ensure it adheres to all rules and regulations surrounding consumer data privacy. As the approach presented in this paper is simply a proof of concept for a facial authentication based digital ID system, the application of data privacy regulation for the hypothetical smart city falls outside the scope of this paper.

TABLE 1. Vulnerable points in DIS.

Serial No.	Type of Attacks	Real World Scenarios
1	Present fraud face bio-metrics at the camera	Using a 3D face mask, 2D photo, a video clip of the attacked face
2	Submit saved digital photo of face instead of using camera	Resubmit earlier photo
3	Trojan Attack during feature extraction	Selection of predefined features by hacker
4	Alter feature set after extraction	When face matching is done at a different place than feature extraction change of some packets in TCP/IP stack remotely
5	Attack the matcher	Matcher shows intruder defined scores
6	Alter the database	Any entry of the database can be changed
7	Attack the channel bringing data from the database	Intercept the channel and alter the data before it reaches matcher
8	Change the final score	Hacker can change the final result failing the FRS

III. NOVEL CONTRIBUTIONS OF THE CURRENT PAPER

Here, the novelty of our work is discussed:

- The user registration process is remotely and securely performed on the edge device. Facial embeddings are extracted using the user's device in an offline application. These embeddings contain no identifiable information and are private by design as they are just a series of numbers generated by a neural network, however they are encrypted for extra protection, and sent to be stored on a remote cloud server operated by the smart city.
- The authentication process is also done on the edge device. The photograph, face embedding extraction, and authentication of the user are all done on the edge. No facial data is sent to the cloud during authentication. It makes the process resilient to various indirect attacks.
- Deep Fakes created by FSGAN pose a serious threat to people due to its fast and easy Deep Fake generation technique. Our system is capable of detecting Deep Fakes created by FSGAN.
- The proposed system can detect presentation attacks. A check is performed each time a user tries to access any facility within the smart city by taking a picture during time of access. This ensures the correct user is present and decreases the risk of presentation attacks. No data is stored anytime in the system during authentication. It is

performed as users come and go. This feature decreases the risk from presentation attacks that are associated with such a system.

- No facial biometric data leaves the edge platform during the authentication phase. No data is stored during authentication. The only data that is stored are the reference facial embeddings extracted during enrolment. These are used to retrain the model on the cloud and never leaves the cloud storage at any time.

IV. RELATED WORKS

In recent years, research on computer vision and pattern recognition has been propelled due to the significant advancement in deep learning techniques, revolutionary parallel computing paradigms, and monumental developments in hardware. As facial authentication is the core of our digital ID system, in this section we refer to some of the recent works on the three main sub parts of the proposed system: various FR systems, face features based authentication, and morphing attack detection (MAD) have been discussed.

A. FR SYSTEMS:

In the early years of facial recognition, a holistic approaches [9] like projection of images on low dimensional space [10], Laplacianface [11], and sparse representation [12] had been followed. In the early 2000s, more local features based face detectors [13], [14] were introduced. However, from 2012 onward high accuracy deep learning based techniques have been predominant. In 2014, DeepFace [15] transformed the direction of facial recognition techniques. An accuracy of 97.35%, close human accuracy, was obtained with this 9-layer deep neural model on the LFW dataset [16].

Deep neural network based techniques have used diverse architectures, different loss functions, and various image processing techniques. In the same year as DeepFace [15], another paper [17] performed face verification using high level features and deep ConvNets. Face features from different face parts helped the model to achieve a higher accuracy of 97.45% on the LFW dataset [16]. Both works used cross-entropy based softmax loss. However, the later versions [18] and [19] of DeepID used an Euclidean distance based loss, contrastive loss. Here, absolute distances of image pairs are calculated.

Another face recognition model is FaceNet [20] where a new loss, triplet loss, was used for feature learning and clustering. The method achieved 99.63% of accuracy. Triplet loss is another Euclidean distance based loss where relative difference of distances between matching pairs is considered. Another important facial recognition system was proposed in [21]. Here, marginal loss was proposed for deep face recognition with a comparable accuracy of 99.48% on the benchmark LFW dataset. It minimizes the intra class variation and maximizes the inter class distances simultaneously.

A pose invariant facial recognition technique was proposed using Disentangled Representation Learning GAN (DR-GAN) in [22]. This FR system has been evaluated for various illumination and angular position of the face. Another competitive FR system is *CosFace* [23]. Large margin cosine loss (LMCL) has been introduced by redefining *Softmax loss* as a *cosine loss*. One of the state-of-the-art FR systems, *ArcFace* is presented in [24]. Additive Angular Margin Loss has been proposed for face recognition. It is a highly accurate system. It achieved the highest accuracy among all the discussed FR systems on the LFW dataset.

B. FACIAL FEATURES BASED AUTHENTICATION SYSTEMS:

In the last few years, various cloud based, cloud-edge based, and IoT mobile device based face authentication systems have been researched in literature.

A detailed survey has been made for face verification and authentication for IoT mobile devices in [25]. In [26], light normalization and information fusion were used for face verification on a mobile device however, no security measures were undertaken. In another work [27], a biometric based security was proposed for IoT infrastructure with a pairing-based cryptography.

A face verification technique for mobile devices is presented in [28]. The Viola-Jones detector has been used for face detection and subspace metrics for authentication. It has a low error rate. But, no security measures were implemented. Another facial feature based active authentication technique for mobile had been proposed in [29]. A short video is used as the input of the face verification system. Detection rate showed a high accuracy only when the authentication and enrolment were done from the same session videos. It is also not suitable for real time use where different sessions data need to be compared. Similarly, a face authentication system for mobile devices is implemented in [30]. Haar like features and the AdaBoost algorithm have been used for face detection and local binary pattern for face authentication.

Another mobile friendly deep learning based face detector had been proposed in [31]. Various illumination and extreme poses were considered. Without CUDA, mobile GPUs have been used to implement deep neural network models. [32] presents a fingerprint and face template based method. The face verification is SVM based whereas the fingerprint verification is minutiae based. According to the authors,"Secure sketch" cryptographic method and geometric translation make the method forgery free. Enhanced biometric-capsule based authentication method was proposed in [33]. MTCNN [34] has been used for face detection and FaceNet [20] has been used for face features extraction. For an IoT-cloud setting, a deep learning based face verification method has been proposed in [35]. The face verification part is done by a tree-based cloud model. The edge part is optional for processing and filtering images.

C. ATTACK DETECTION:

In this subsection, we discuss papers addressing various attacks in facial recognition systems. User liveness has been addressed in a majority of the papers .

For face authentication, an acoustic sensor based liveness detection method has been proposed in [36] with an accuracy of 96.02% and false alarm rate of 3.97%. It uses unevenness of the stereo structure of real face to check liveness of the user. Another liveness detection method has been proposed in [37] using photoplethysmograms of two simultaneous videos of face and fingertips.

Some papers also focus on the Deep Fakes detection systems. In [38] and [39] Deep Fake videos have been detected. These convolutional network based works present high accuracies. Dynamic lip movement analysis has been done in [40] to detect Deep Fake attack. In [41], the potential threat of face swapping to electronic Know Your Customer (eKYC) has been discussed and a detection system has been proposed. Another IoT friendly Deep Fake detection method has been described in [42]. Features from Gray Level Co-occurrence Matrix (GLCM) have been utilized along with LightGBM classifier. In [43], an anti spoofing facial recognition system has been proposed. COTS RFID tag array has been used to extract biometric features of face and 3D geometry. 95.7% success rate is achieved with 4.4% EER.

From the above discussion it is clear, a number of state-of-the-art FR systems, various cloud / edge-cloud / mobile based facial authentication methods, and different attack detection techniques have been introduced in last few years. Regardless of all the state-of-the-art methods, no end-to-end facial authentication system which can be used for implementing a digital ID system for smart cities has been proposed. Our objective is to propose a proof-of-concept of a viable but simple facial authentication based digital ID system for smart cities with high success rates in detecting attacks and authenticating smart city citizens.

V. IFACE 1.1 : PROPOSED FACIAL AUTHENTICATION BASED DIGITAL ID SYSTEM OF SMART CITIES

iFace 1.1 is the proposed digital ID system for smart cities. It would allow residents to access various amenities of the city once facial authentication is performed.

A. SYSTEM LEVEL ARCHITECTURE

iFace 1.1 is presented as a four layered architecture which is spread between edge and cloud platforms, as shown in Fig.3.

1) Layer-1: Input layer of the authentication system is denoted as layer-1. In this level, smart city residents capture photos using the cameras attached to their personal devices. The photo is then sent for authentication into layer-2. Users also provide their username.
2) Layer-2: Layer-2 is the edge computing platform. Here, the photo along with the username from the previous layer works as the input of this layer. No data is transmitted at this stage over the open communication channels as both the layers are located on the same device. Hence, no encryption of facial data is required at this stage. Layer-2 handles the data processing and computing part of iFace 1.1.
3) Layer-3: The cloud computing platform is the third layer. Long range communication technologies like *4G*, *LTE* connects the edge devices to this layer. During registration, biometric data is transmitted to this layer after encrypting at layer-2. Bio-metric data and usernames are stored in this layer.
4) Layer-4: The last layer consists of smart city stakeholders like various facilities of smart cities. Residents can avail different amenities after they are authenticated with the iFace 1.1 system.

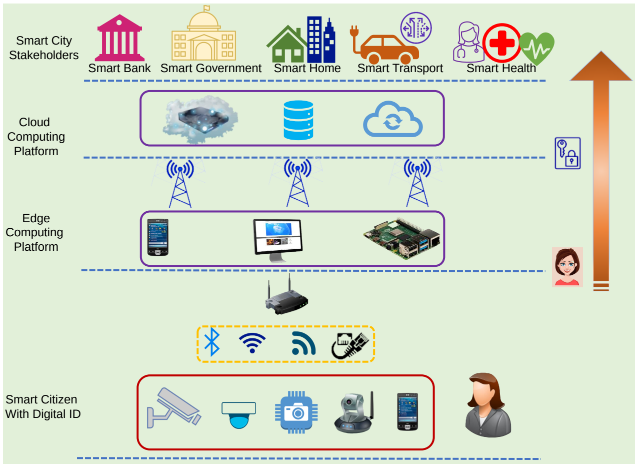


FIGURE 3. End-to-End System Level Framework of iFace 1.1

B. SYSTEM OVERVIEW

The aim of the paper is to propose a proof-of-concept of a working end-to-end digital ID system which can be implemented in a smart city. The ID system works in two phases:

- Registration/Enrolment Phase
- Authentication Phase

1) Enrolment Phase

The registration process of a new applicant is shown in Fig. 4. In this phase, an existing government issued ID is checked for any forgery. Then a unique username is provided to the new applicant.

A neutral frontal face (NFF) image is taken by the edge device camera. Next, the face is detected in the image by the face detection (FD) module. The photo is then checked for Deep Fake and presentation attacks in the Attack Detection (AD) module. If the AD module does not verify the photo, law enforcement authorities are notified for possible fraud. For legitimate applicants, a facial embedding is extracted from the detected face of the photo. The embedding along with username is added to a Look Up table on the cloud server of the smart city. Data encryption may be added at this step.

2) Authentication Phase

Authentication is done on the edge as in Fig. 5. The user provides their username and a photo is captured by the edge

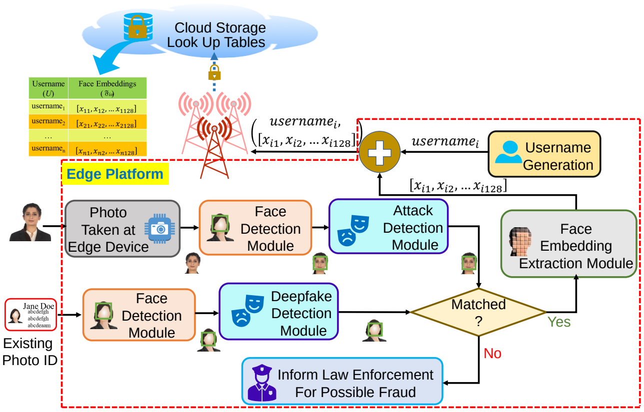


FIGURE 4. New User Registration

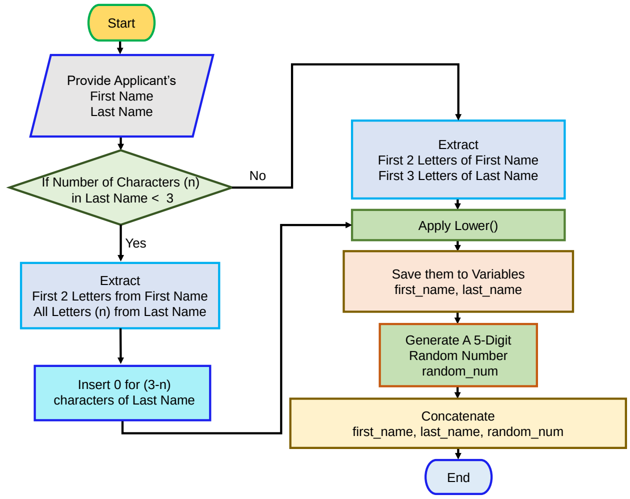


FIGURE 6. Username Generation Module Workflow

device. Once the face is detected in the FD module, it is checked for any possible attack in the AD module. Next, the facial embedding is extracted and the system predicts the username associated with the face embedding. If the predicted username is matched with the input username, access to the facility is granted otherwise it is denied.

Look Up Table	
Username	**Face Embedding**
abcde02846	$[x_{11}, x_{12}, ... x_{1128}]$
fghij96784	$[x_{21}, x_{22}, ... x_{2128}]$
...	...
klmn069001	$[x_{n1}, x_{n2}, ... x_{n128}]$

FIGURE 7. Sample Look Up Table

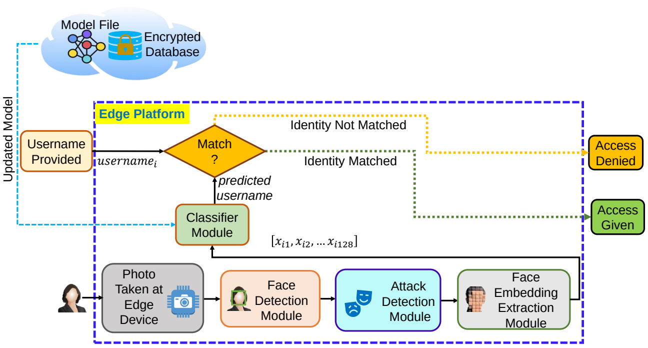


FIGURE 5. Authentication at Edge.

C. SYSTEM MODULES

The system pipeline consists of various modules. Each module serves a specific purpose.

1) Username Generation (UG) Module

The UG module is an important module where unique and user specific usernames are generated during registration. Fig.6 shows a sample username generation module workflow. During registration, the applicant provides their name. A unique username is generated as per the sample workflow.

During enrolment, the generated username and facial embedding extracted from the photo are sent to the cloud data storage and added to the look up table. Data encryption should be used in each step to make the process more secure. Fig. 7 shows a sample look up table before encryption. The stored data is used to train the classifier time to time.

2) Face Detection (FD) Module

Accurate face detection is the first step of face authentication. There are mainly two types of state-of-the-art face detection methods: deep neural network based and handcrafted features based or machine learning based. Deep neural network based face detectors e.g., Multitask cascaded CNN [44], RetinaFace [45], Fast RCNN [46], Faster RCNN [47], Mask RCNN [48], YOLO [49], and SSD [50] have emerged as successful face detectors. They are more accurate and robust. But the majority of them are heavy and relatively unsuitable for deployment on an embedded device.

In our work, a light weight, fast, and efficient model is required. Hence, we choose a machine learning based face detector over a deep neural network based one. The face detector should not work under any face occlusion for security and data integrity purpose. Face detection from the frontal face photo is required. Hence, the Viola-Jones Haar Cascade face detector [51] has been chosen as the face detection module from [14], [51]–[53]. It detects the face from the photo. It is tiny in size ($\sim$ 1MB) so a good fit for an IoT environment where resources are limited. It does not work under conditions where the face is occluded which is a mandatory condition of the system to avoid any fraudulent activity. Dlib HoG [54] face detector also works with mostly

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3187686

frontal face. But, the extracted face by Dlib HoG mostly excludes the forehead of the detected face as shown in Fig. 8. It is not desired for face authentication purpose.

Therefore, a frontal face image is necessary each time for security reasons. But for practical implementation, an alternative state-of-the-art suitable method can be used.

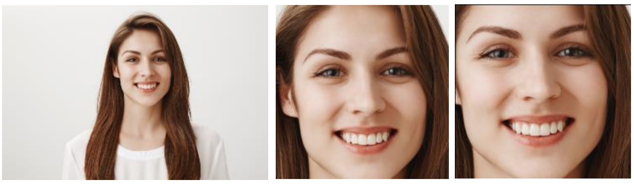
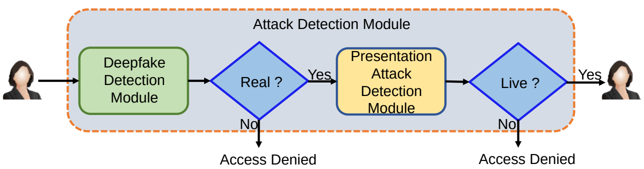


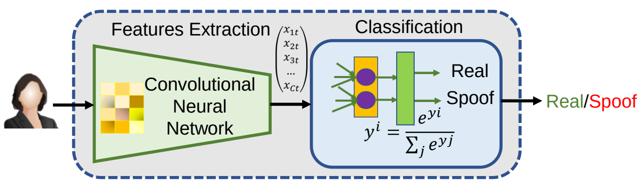
FIGURE 8. Extracted Faces using Haar Cascade (Middle) and Dlib HoG (Right Most) Face Detectors From Original Face (Left Most) (Photo Courtesy: Microsoft Power Point)

3) Attack Detection (AD) Module

The attack detection module is the next module in the digital ID system pipeline. It checks for various presentation attacks. A person with ill intention can gain access to any facility in smart city by fooling the facial recognition systems. A spoof image or non living object can be presented to the camera of the edge device instead of a live person. To detect such attack, the neutral frontal face photo of the user, taken through the edge device camera, is passed through the AD module as in Fig. 9(a). AD module comprises of two subsystems - the Deepfake Detection (DD) and Presentation Attack Detection (PAD) modules.



(a) System Level Diagram of Attack Detection Module



(b) Detection Process

FIGURE 9. Attack Detection Module

a: Deepfake Detection (DD) Module

The Deep Fake detection(DD) module is used to detect if there is a deep fake attack on the system. Ideally the module should be trained to detect any type of Deep Fake. However, for the purposes of this proof-of-concept, the model has been trained to only detect Deep Fakes, generated by face swapping techniques. More research on deep fakes is needed to propose a generalized Deep Fake detection module.

We follow the procedure shown in Fig. 9(b) from [55] to detect the Deep Fakes. As MobileNetV2 [56] is suitable for an edge platform, pre-trained MobileNetV2 is finetuned to extract the distinguishing features of the images. The last layer of MobileNetV2 structure is replaced by a fully connected layer with Softmax activation and 2 nodes, and used as a classifier as [39], [38]. Binary cross entropy loss has been used for training.

DeepfakeTIMIT (DFTIMIT) [6], [57] dataset for fake images and VidTIMIT [58] for real images have been used for training and validation of the DD module, as shown in Table. 2. The dataset has been split into 80% train and 20% validation.

TABLE 2. Datasets for Deepfake Detection Module

Dataset	Image Type	No. of Images	Remarks
VidTIMIT	Real	34,004	10 videos taken at 3 settings for 32 subjects have been used.
DeepfakeTIMIT (HQ)	Fake	33,988	Total 620 videos of 32 subjects have been used. Image extraction rate 25 fps
DeepfakeTIMIT (LQ)	Fake	34,025	

The classifier layer was trained for 10 epochs and then the end-to-end model is trained for 15 more epochs. The best model is evaluated as per the validation accuracy. The same and cross dataset evaluation has been performed.

Table. 3 presents the accuracy obtained for the Deepfake Detection module. Perfect accuracy is achieved when the model is trained and evaluated on DF-TIMIT (LQ) and VidTIMIT datasets. But in a real scenario, we counter with high quality fraud. When the testing data is high quality such that it resembles reality, we achieve a more realistic accuracy of 94.83% meaning our system can detect 94.83% face swap Deep Fake images.

TABLE 3. Accuracy of Deepfake Detection Module for Different Evaluation Scenarios

Training Dataset	Testing Dataset	Accuracy (%)
DF-TIMIT (LQ)	DF-TIMIT (LQ)	100.00
DF-TIMIT (HQ)	DF-TIMIT (HQ)	94.83
DF-TIMIT (HQ)	DF-TIMIT (LQ)	96.91

* For real images → VidTIMIT dataset.

b: Presentation Attack Detection (PAD) Module

To detect presentation attacks, the same pipeline shown in Fig. 9(b) is followed. Here we use EfficientNet B0 [59] as the feature extractor as it shows better results. A GlobalAveragePooling layer, followed by a dense layer of 2 nodes and a Softmax activation function, have been used as the classifier. As presentation attacks have been approached as a binary classification problem, Binary Cross Entropy loss has been used. Here also, transfer learning is used to reduce the training time and to achieve higher accuracy.

Replay Attack dataset [60] has been used to train and evaluate the Presentation Attack Detection module. The Dataset is an imbalanced one. For our work we partially used the spoof part of the dataset to make a balanced dataset. The dataset details used in our work has been stated in Table 4. The number of frames extracted from test videos are fewer than train videos as duration of the test videos are shorter than train videos in the dataset. Frames have been extracted using ffmpeg [61].

TABLE 4. Dataset for Presentation Attack Detection Module

Dataset	Type	Image Type	No. of Images	Remarks
Replay Attack	Train	Real	899	60 original train videos
		Spoof	891	120 spoof videos
	Test	Real	80	80 original test videos
		Spoof	191	200 spoof test videos

Here the initial number of epochs for the classifier training is kept to 5 and 10 for end-to-end model training. No data augmentation has been done. The model has been evaluated with the test section of Replay Attack [60] dataset.

Our system can detect 93.0% presentation attacks. The performance of the module is evaluated through *Confusion Matrix* in Fig. 10. *Precision*, *Recall*, *F1-Score*, and *Accuracy* have been calculated in Table. 5.

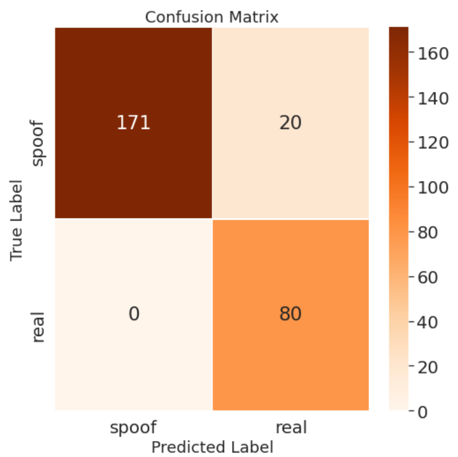


FIGURE 10. Confusion Matrix for Presentation Attack Module

TABLE 5. Classification Report of Presentation Attack Module -Trained and Tested on Replay Attack Dataset

Test images	Precision (%)	Recall (%)	F1-score
191 Spoof	100.0	90.0	94.0
80 Real	80.0	100.0	89.0
Macro Average	90.0	95.0	92.0
Weighted Average	94.0	93.0	93.0
Total 271	**Accuracy (%)**	93.0	

4) Face Features Extraction (FFE) Module

One of the major modules of the system is the feature extraction module as it extracts the face features from an image. We wanted to select a simple but highly accurate method as the Face Features Extraction (FFE) module. Hence, we followed the process as in FaceNet [20] instead of other new state-of-the-art methods to extract face features. In image classification, state-of-the-art accuracy has been obtained in Google's EfficientNets. The model size and computational complexity are notably low. Therefore, instead of using the original deep learning network of FaceNet, we use EfficientNet B0 as the feature extractor [62].

Fig. 11 shows the workflow diagram of the FFE module at training. We use EfficientNet B0 [59], pretrained on ImageNet as the backbone feature extractor, and connect a GlobalAveragePooling layer followed by a dense layer of 128 nodes and without any activation function. L2 normalization is used to extract face embedding as in [20]. The module extracts face features from the face image. These features are expressed in terms of a 128-dimensional feature vector.

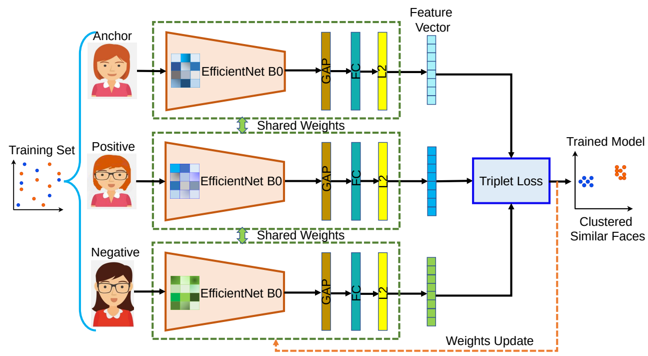


FIGURE 11. Training of Face Features Extraction Module

The Triplet Loss function [20] has been used to train the feature extraction module. During training, the network learns to measure the optimum Euclidean distance among images through the embedding.

Once the feature extractor is trained, face embeddings of the test image are extracted using the trained model.

To train the face features extraction module, we downloaded images of the main characters of American sitcom 'Friends' using Bing Search API and made a customized dataset. The dataset details are mentioned in Table. 6. We used images without any occlusion in the face.

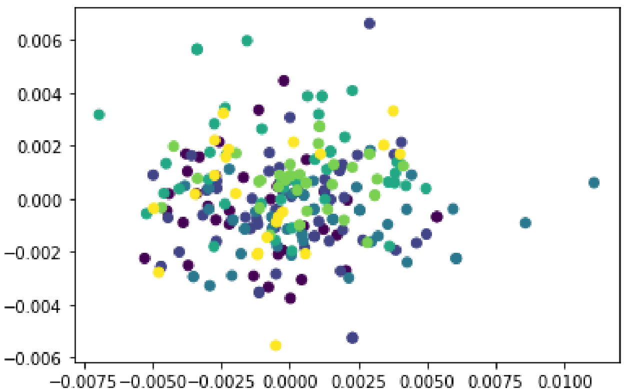
TABLE 6. Customized Dataset for Face Features Extraction Module and Classification Module

Dataset	Image Type	No. of Images
Main 6 Characters of American sitcom 'Friends'	Chandler	45
	Joey	50
	Monica	47
	Phoebe	43
	Rachel	36
	Ross	30

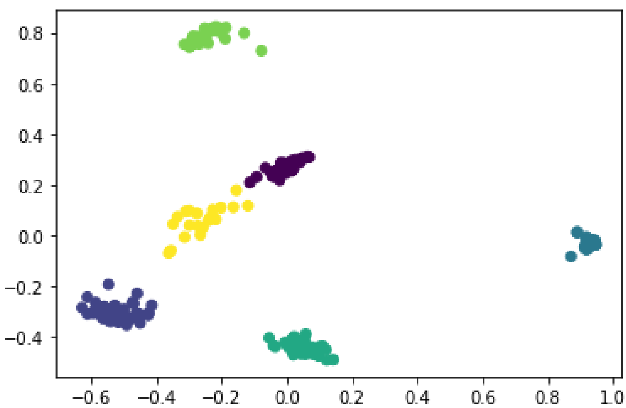
This module is trained for 100 epochs. A set of triplets i.e. anchor image, positive image, and negative image are generated before training. To generate the triplets, the below procedure has been followed-

1) For our dataset we have 6 classes (6 characters). 2 classes are chosen randomly.
2) 2 images are chosen from one class and 1 image is selected from the other class. This process is also random. From 2 images, one is chosen randomly as the anchor image and the other as the positive image whereas the single image from the other class is chosen as the negative image.
3) For each anchor image we chose 10 positive and 10 negative random images. So for our 247 images 24,700 combinations of triplets are generated.

Fig. 12 shows the Principal Component Analysis (PCA) plot of the embeddings of our training dataset for the Face Features Extraction Module. Here, 2 principal components are used to reduce the dimensionality of the embedding vectors. Fig. 12(a) shows the embeddings before training the module and Fig. 12(b) shows the same embeddings, clustered after the training.



(a) Before Training



(b) After Training

FIGURE 12. Embedding Plots of Six Main Characters of American Sitcom 'Friends'

5) Classifier

Once the Face Features Extraction module extracts the features, a classifier is used to predict the identity of the image. In our work, a k-Nearest Neighbor (kNN) classifier with 3 neighbors, auto tree algorithm, and 30 leaves is used to make the prediction. The distance metric of the classifier is chosen as *Euclidean*. We train the classifier with the face embedding extracted from the trained FFE module. It authenticates or denies a face by measuring the distance to k nearest neighbours and finally decides by taking a majority voting. Fig.13 shows the training of the classifier. The classifier predicts the username corresponding to the face embedding.

Embeddings from face features extraction module are used as the training data for classification. The dataset details are mentioned in Table. 6.

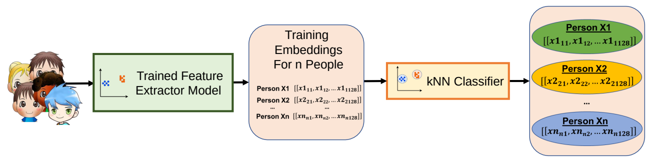


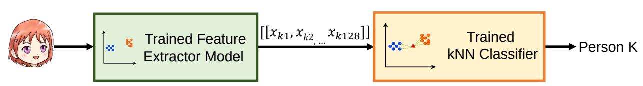
FIGURE 13. Classifier Training

Embeddings from the trained FFE module are used as the input of the classifier. So, the number of training images of the classifier is equal to the number of original images i.e. 247.

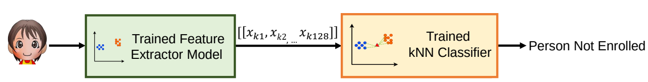
VI. PERFORMANCE OF THE PROPOSED DIGITAL ID FACE AUTHENTICATION SYSTEM

The user is authenticated in an intuitive way by comparing the input username with the predicted username from the face embeddings extracted during authentication at the smart device. This authentication is carried out on the edge.

Fig. 14 shows the authentication process. If the person is already enrolled in the system and the predicted username matches with the input username the classifier authenticates as in Fig. 14(a). The person gets access to the facility. But if the person is not enrolled in the system or the predicted username does not match with the input username, the system does not give access of the facility to the person as in Fig. 14(b).



(a) Person In System



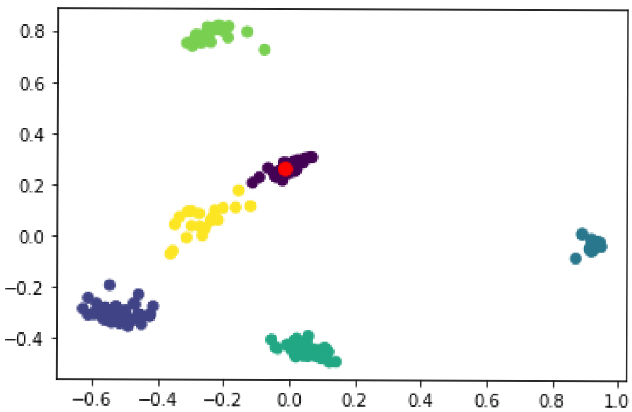
(b) Person Not In System

FIGURE 14. Authentication Process

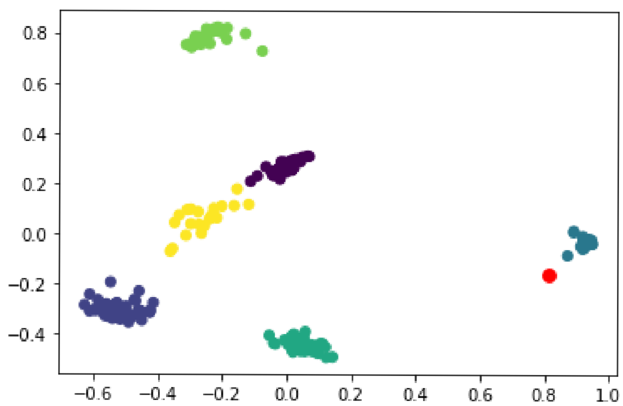
This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3187686

During authentication, data collection, processing, feature extraction, and prediction are all done on the edge platform. As user verification is carried out each time the user accesses the facilities, the odds of impersonating a person are very low. This provision makes the system robust. Encryption during data transfer and storage further secures the system.

When a face needs to be authenticated in the system, the embedding is extracted from the image through the trained FFE module. Two such scenarios are plotted in PCA plots as in Fig. 15 along with training data embeddings. If the person is already enrolled in the system, the PCA plot is as in Fig. 15(a) and if the user is not yet enrolled in the system, Fig. 15(b) depicts that scenario. 171 spoofs have been correctly detected among 191 spoof images.



(a) For Enrolled Person



(b) For Not Enrolled Person

FIGURE 15. Embedding Plot of Sample Person in the Clustered Training Dataset

The system has been tested with 50 unseen frontal images of 6 enrolled people and 500 frontal images of CelebA [63] dataset. The first set is also used as the authorized people to measure false rejection ratio (FRR) and the second set as the intruder to measure false acceptance ratio (FAR).

Table. 7 and Fig. 16 show the performance of the facial recognition system of proposed digital ID. FRR is calculated with 50 images of enrolled people. One among 50 images was falsely rejected generating FRR of 2%. We evaluate the system with 500 images from CelebA [63] dataset. 15 images were falsely accepted. FAR is calculated to 3%.

The tested images are not all frontal face. The foreheads or cheeks of some faces are occluded with hair. Those images are the cause of the false acceptance ratio. There is a variation of age for certain 'Friends' characters in our training and testing dataset. This was intentionally chosen to see the effect of aging of a person in his/her digital ID.

TABLE 7. Performance of the Proposed Digital ID

Dataset	Type	No. of Test Images	No. of Authentication		
			Correct	False Acceptance	False Rejection
Own Data	Enrolled User	50	49	0	1
CelebA	Not Enrolled User	500	485	15	0

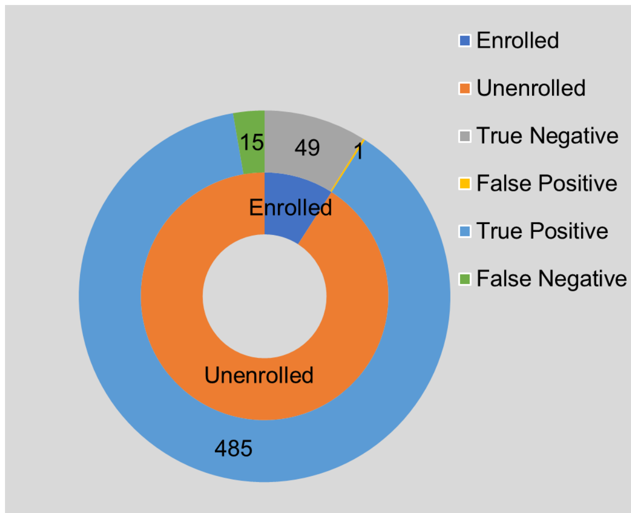


FIGURE 16. Digital ID Performance

Various metrics like *Precision*, *Recall*, *F1-Score*, *Accuracy*, *FRR*, and *FAR* have been calculated in Table. 8 to evaluate the digital ID system.

TABLE 8. Performance Metrics of Facial Authentication System

Test images	Precision (%)	Recall (%)	F1-score
500 Impostors	100.0	70.0	98.0
50 Users	77.0	98.0	86.0
Macro Average	88.0	97.0	92.0
Weighted Average	98.0	97.0	97.0
Total 550	**Accuracy (%)**	97.0	
	FRR	2.0	
	FAR	3.0	

VII. CONCLUSION AND FUTURE WORK

In this article, a proof-of-concept of an end-to-end facial authentication based digital ID system for smart cities has been proposed. Here, several things have been accomplished:

- Our system can detect various intruder attacks mentioned in Sections II-B1a and II-B1b. The system is deepmorph deepfake attack, mentioned in Section II-B1b, resilient. It shows high accuracy even with high quality face swapped GAN generated images.
- It can detect presentation attacks, mentioned in Section II-B1a, with an accuracy of 93%.
- False acceptance ratio and false rejection ratio of the system are fairly low.
- The face authentication system has an accuracy of 97%. As facial authentication has been done at the edge, the risk of security compromise is reduced.
- No photos are stored anywhere in the system. Face features are stored at the cloud in terms of a numerical value. Hence, it is not possible to reverse engineer the photos from these numbers which makes the process secured.
- Biometric data are stored without any identifiable information of the user eliminating the data privacy regulation issues.

A re-enrolment of face features is needed if the person significantly ages to accommodate the age related changes of the person. Data deletion processes need to be included in the system after someone's death. If there is any facial change due to any accident or cosmetic surgery, a data update option needs to be there. The provision for deletion of data and re-enrolment of the user with a new user id should be incorporated in case of identity theft.

As a future work, a more efficient digital ID system can be achieved by upgrading the modules and the facial authentication system to state-of-the-art systems.

Currently, the deepfake attack detection module detects the face swapped images. It can be extended to a comprehensive model which will detect deepfakes generated by other GANs. To obtain a generalized model, a very large dataset of human faces is required with images generated by various GANs. People of different demographics, races, color, gender, and ages should be included in the systems. People with glasses, piercings, head coverings, hearing aids, and braces should also be included in the training dataset. The hardware should support this lengthy and resource extensive training.

The existing PAD module detects spoofs from the face photo. The PAD module needs to be experimented with different head poses [64], lighting conditions [65], inside, outside, day, and night settings. It can be improved by using challenge response techniques with random instructions for motion e.g., head and eye movement, opening and closing mouth or reading out loud any random sentences. Voice verification can also be added to enhance one more level of verification. The system should be capable of authenticating people with face occlusions such as sunglasses, masks, and any facial piercings. It will be exciting to see if identical twin scenario can be addressed.

To the authors' best knowledge, iFace 1.1 is the first viable end-to-end proof-of-concept that addresses the main challenges of smart-city digital ID. We hope to see more researches on this direction and finally an implemented iFace system in a smart city.

ACKNOWLEDGMENT

A short conference version of this work was presented at [3]

REFERENCES

[1] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The Internet of things is the backbone," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, 2016, doi: 10.1109/MCE.2016.2556879.

[2] "Report: Cisco and IBM leaders in the smart cities technology market," November 21, 2014, Accessed: February 24, 2022. [Online]. Available: https://www.smartcitiescouncil.com/article/report-cisco-and-ibm-leaders-smart-cities-technology-market

[3] A. Mitra, S. P. Mohanty, P. Corcoran, and E. Kougianos, "iFace: A Deepfake Resilient Digital Identification Framework for Smart Cities," in *Proc. IEEE International Symposium on Smart Electronic Systems (iSES)*, 2021, pp. 361–366, doi: 10.1109/iSES52644.2021.00090.

[4] N. K. Ratha, J. H. Connell, and R. M. Bolle, "Enhancing security and privacy in biometrics-based authentication systems," *IBM Systems Journal*, vol. 40, no. 3, pp. 614–634, 2001, doi: 10.1147/sj.403.0614.

[5] J. Hernandez-Ortega, J. Fierrez, A. Morales, and J. Galbally, "Introduction to Presentation Attack Detection in Face Biometrics and Recent Advances," 2021. [Online]. Available: https://arxiv.org/abs/2111.11794

[6] P. Korshunov and S. Marcel, "DeepFakes: a New Threat to Face Recognition? Assessment and Detection," 2018. [Online]. Available: https://arxiv.org/abs/1812.08685

[7] Y. Nirkin, Y. Keller, and T. Hassner, "FSGAN: Subject Agnostic Face Swapping and Reenactment," 2019. [Online]. Available: https://arxiv.org/abs/1908.05932

[8] S. P. Mohanty, "Security and Privacy by Design is Key in the Internet of Everything (IoE) Era," *IEEE Consumer Electronics Magazine*, vol. 9, no. 2, pp. 4–5, 2020, doi: 10.1109/MCE.2019.2954959.

[9] M. Wang and W. Deng, "Deep face recognition: A survey," *Neurocomputing*, vol. 429, pp. 215–244, 2021, doi: https://doi.org/10.1016/j.neucom.2020.10.081.

[10] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 19, no. 7, pp. 711–720, 1997, doi: 10.1109/34.598228.

[11] X. He, S. Yan, Y. Hu, P. Niyogi, and H.-J. Zhang, "Face recognition using Laplacianfaces," *IEEE transactions on pattern analysis and machine intelligence*, vol. 27, no. 3, pp. 328–340, 2005, doi: 10.1109/TPAMI.2005.55.

[12] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust Face Recognition via Sparse Representation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 31, no. 2, pp. 210–227, 2008, doi: 10.1109/TPAMI.2008.79.

[13] C. Liu and H. Wechsler, "Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition," *IEEE Transactions on Image processing*, vol. 11, no. 4, pp. 467–476, 2002, doi: 10.1109/TIP.2002.999679.

[14] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE transactions on pattern analysis and machine intelligence*, vol. 28, no. 12, pp. 2037–2041, 2006, doi: 10.1109/TPAMI.2006.244.

[15] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," in *Proc. IEEE conference on computer vision and pattern recognition*, 2014, pp. 1701–1708, doi: 10.1109/CVPR.2014.220.

[16] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, "Labeled faces in the wild: A database for studying face recognition in unconstrained environments," University of Massachusetts, Amherst, Tech. Rep. 07-49, October 2007.

[17] Y. Sun, X. Wang, and X. Tang, "Deep Learning Face Representation from Predicting 10,000 Classes," in *Proc. IEEE conference on computer vision and pattern recognition*, 2014, pp. 1891–1898, doi: 10.1109/CVPR.2014.244.

[18] Y. Sun, X. Wang, and X. Tang, "Deep learning face representation by joint identification-verification," 2014, doi: 10.48550/ARXIV.1406.4773. [Online]. Available: https://arxiv.org/abs/1406.4773

[19] Y. Sun, X. Wang, and X. Tang, "Deeply learned face representations are sparse, selective, and robust," 2014, doi: 10.48550/ARXIV.1412.1265. [Online]. Available: https://arxiv.org/abs/1412.1265

[20] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 815–823, doi: 10.1109/CVPR.2015.7298682.

[21] J. Deng, Y. Zhou, and S. Zafeiriou, "Marginal Loss for Deep Face Recognition," in *Proc. IEEE conference on computer vision and pattern recognition workshops*, 2017, pp. 60–68, doi: 10.1109/CVPRW.2017.251.

[22] L. Tran, X. Yin, and X. Liu, "Disentangled Representation Learning GAN for Pose-Invariant Face Recognition," in *Proc. IEEE conference on computer vision and pattern recognition*, 2017, pp. 1415–1424, doi: 10.1109/CVPR.2017.141.

[23] H. Wang, Y. Wang, Z. Zhou, X. Ji, D. Gong, J. Zhou, Z. Li, and W. Liu, "CosFace: Large Margin Cosine Loss for Deep Face Recognition," in *Proc. IEEE conference on computer vision and pattern recognition*, 2018, pp. 5265–5274, doi: 10.1109/CVPR.2018.00552.

[24] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "Arcface: Additive Angular Margin Loss for Deep Face Recognition," in *Proc. the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4690–4699, doi: 10.1109/CVPR.2019.00482.

[25] M. A. Ferrag, L. Maglaras, and A. Derhab, "Authentication and authorization for mobile IoT devices using biofeatures: Recent advances and future trends," *Security and Communication Networks*, vol. 2019, p. 20 pages, 2019, doi: https://doi.org/10.1155/2019/5452870.

[26] Q. Tao and R. Veldhuis, "Biometric Authentication System on Mobile Personal Devices," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 4, pp. 763–773, 2010, doi: 10.1109/TIM.2009.2037873.

[27] M. S. Hossain, G. Muhammad, S. M. M. Rahman, W. Abdul, A. Alelaiwi, and A. Alamri, "Toward end-to-end biomet rics-based security for IoT infrastructure," *IEEE Wireless Communications*, vol. 23, no. 5, pp. 44–51, 2016, doi: 10.1109/MWC.2016.7721741.

[28] Q. Tao and R. N. Veldhuis, "Biometric Authentication for a Mobile Personal Device," in *Proc. 3rd Annual International Conference on Mobile and Ubiquitous Systems - Workshops*, 2006, pp. 1–3, doi: 10.1109/MOBIQW.2006.361741.

[29] M. E. Fathy, V. M. Patel, and R. Chellappa, "Face-based active authentication on mobile devices," in *Proc. IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 2015, pp. 1687–1691, doi: 10.1109/ICASSP.2015.7178258.

[30] A. Hadid, J. Y. Heikkila, O. Silven, and M. Pietikainen, "Face and Eye Detection for Person Authentication in Mobile Phones," in *Proc. First ACM/IEEE International Conference on Distributed Smart Cameras*, 2007, pp. 101–108, doi: 10.1109/ICDSC.2007.4357512.

[31] S. Sarkar, V. M. Patel, and R. Chellappa, "Deep feature-based face detection on mobile devices," in *Proce. IEEE International Conference on Identity, Security and Behavior Analysis (ISBA)*, 2016, pp. 1–8, doi: 10.1109/ISBA.2016.7477230.

[32] Y. Sutcu, Q. Li, and N. Memon, "Secure biometric templates from fingerprint-face features," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1–6, doi: 10.1109/CVPR.2007.383385.

[33] T. Phillips, X. Zou, F. Li, and N. Li, "Enhancing Biometric-Capsule-Based Authentication and Facial Recognition via Deep Learning," in *Proc. 24th ACM Symposium on Access Control Models and Technologies*, ser. SACMAT '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 141–146, doi: 10.1145/3322431.3325417.

[34] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multi-task cascaded convolutional networks," *CoRR*, vol. abs/1604.02878, 2016.

[35] M. Masud, G. Muhammad, H. Alhumyani, S. S. Alshamrani, O. Cheikhrouhou, S. Ibrahim, and M. S. Hossain, "Deep learning-based intelligent face recognition in IoT-cloud environment," *Computer Communications*, vol. 152, pp. 215–222, 2020, doi: https://doi.org/10.1016/j.comcom.2020.01.050.

[36] H. Chen, W. Wang, J. Zhang, and Q. Zhang, "EchoFace: Acoustic Sensor-Based Media Attack Detection for Face Authentication," *IEEE Internet of Things Journal*, vol. 7, no. 3, pp. 2152–2159, 2020, doi: 10.1109/JIOT.2019.2959203.

[37] Y. Chen, J. Sun, X. Jin, T. Li, R. Zhang, and Y. Zhang, "Your face your heart: Secure mobile face authentication with photoplethysmograms," in *Proc. IEEE INFOCOM 2017 - IEEE Conference on Computer Communications*, 2017, pp. 1–9, doi: 10.1109/INFOCOM.2017.8057220.

[38] A. Mitra, S. P. Mohanty, P. Corcoran, and E. Kougianos, "A Novel Machine Learning based Method for Deepfake Video Detection in Social Media," in *Proc. IEEE International Symposium on Smart Electronic Systems (iSES)*, 2020, pp. 91–96, doi: 10.1109/iSES50453.2020.00031.

[39] Alakananda Mitra, S. P. Mohanty, P. Corcoran, and E. Kougianos, "A Machine Learning Based Approach for Deepfake Detection in Social Media Through Key Video Frame Extraction," *SN Comput. Sci.*, vol. 2, no. 2, p. 98, 2021, doi: 10.1007/s42979-021-00495-x.

[40] C.-Z. Yang, J. Ma, S. Wang, and A. W.-C. Liew, "Preventing DeepFake Attacks on Speaker Authentication by Dynamic Lip Movement Analysis," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 1841–1854, 2021, doi: 10.1109/TIFS.2020.3045937.

[41] T.-L. Do, M.-K. Tran, H. H. Nguyen, and M.-T. Tran, "Potential Threat of Face Swapping to eKYC with Face Registration and Augmented Solution with Deepfake Detection," in *Future Data and Security Engineering*, T. K. Dang, J. Küng, T. M. Chung, and M. Takizawa, Eds. Cham: Springer International Publishing, 2021, pp. 293–307, doi: https://doi.org/10.1007/978-3-030-91387-8_19.

[42] A. Mitra, S. P. Mohanty, P. Corcoran, and E. Kougianos, "EasyDeep: An IoT Friendly Robust Detection Method for GAN Generated Deepfake Images in Social Media," in *Internet of Things. Technology and Applications*, L. M. Camarinha-Matos, G. Heijenk, S. Katkoori, and L. Strous, Eds. Cham: Springer International Publishing, 2022, pp. 217–236, doi: https://doi.org/10.1007/978-3-030-96466-5_14.

[43] W. Xu, J. Liu, S. Zhang, Y. Zheng, F. Lin, J. Han, F. Xiao, and K. Ren, "RFace: Anti-Spoofing Facial Authentication Using COTS RFID," in *Proc. IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, 2021, pp. 1–10, doi: 10.1109/INFOCOM42981.2021.9488737.

[44] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multitask cascaded convolutional networks," *IEEE signal processing letters*, vol. 23, no. 10, pp. 1499–1503, 2016, doi: 10.1109/LSP.2016.2603342.

[45] J. Deng, J. Guo, E. Ververas, I. Kotsia, and S. Zafeiriou, "Retinaface: Single-Shot Multi-Level Face Localisation in the Wild," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 5203–5212, doi: 10.1109/CVPR42600.2020.00525.

[46] R. Girshick, "Fast R-CNN," 2015, doi: 10.48550/ARXIV.1504.08083. [Online]. Available: https://arxiv.org/abs/1504.08083

[47] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in *Advances in Neural Information Processing Systems*, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015.

[48] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," 2017, doi: 10.48550/ARXIV.1703.06870. [Online]. Available: https://arxiv.org/abs/1703.06870

[49] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Proc. IEEE conference on computer vision and pattern recognition*, 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

[50] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, "SSD: Single Shot Multibox Detector," in *European conference on computer vision*. Springer, 2016, pp. 21–37, doi: https://doi.org/10.1007/978-3-319-46448-0_2.

[51] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, vol. 1, 2001, pp. I–I, doi: 10.1109/CVPR.2001.990517.

[52] P. Viola and M. J. Jones, "Robust real-time face detection," *International journal of computer vision*, vol. 57, no. 2, pp. 137–154, 2004, doi: https://doi.org/10.1023/B:VISI.0000013087.49260.fb.

[53] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, vol. 1. IEEE, 2005, pp. 886–893, doi: 10.1109/CVPR.2005.177.

[54] D. E. King, "Dlib-Ml: A Machine Learning Toolkit," *J. Mach. Learn. Res.*, vol. 10, p. 1755–1758, Dec 2009.

[55] A. Mitra, S. P. Mohanty, P. Corcoran, and E. Kougianos, "Detection of Deep-Morphed Deepfake Images to Make Robust Automatic Facial Recognition Systems," in *Proc. 19th OITS International Conference on Information Technology (OCIT)*, 2021, pp. 149–154, doi: 10.1109/OCIT53463.2021.00039.

[56] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proc.*

IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.

[57] P. Korshunov and S. Marcel, "DeepFakes: a New Threat to Face Recognition? Assessment and Detection," Idiap, Idiap-RR Idiap-RR-18-2018, 12 2018, http://publications.idiap.ch/attachments/reports/2018/Korshunov_Idiap-RR-18-2018.pdf.

[58] C. Sanderson and B. Lovell, "Multi-Region Probabilistic Histograms for Robust and Scalable Identity Inference," Lecture Notes in Computer Science (LNCS), Vol. 5558, pp. 199–208, 2009, doi: https://doi.org/10.1007/978-3-642-01793-3_21.

[59] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," 2019. [Online]. Available: https://arxiv.org/abs/1905.11946

[60] I. Chingovska, A. Anjos, and S. Marcel, "On the effectiveness of local binary patterns in face anti-spoofing," in *Proc. the International Conference of Biometrics Special Interest Group (BIOSIG)*, 2012, pp. 1–7.

[61] S. Tomar, "Converting video formats with FFmpeg," *Linux Journal*, vol. 2006, no. 146, p. 10, 2006.

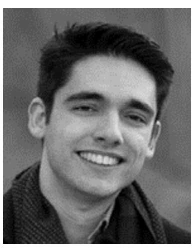
[62] S. Gupta and M. Tan, "EfficientNet-EdgeTPU: Creating Accelerator-Optimized Neural Networks with AutoML ," https://ai.googleblog.com/2019/08/efficientnet-edgetpu-creating.html, Accessed: January 30, 2022.

[63] Z. Liu, P. Luo, X. Wang, and X. Tang, "Deep Learning Face Attributes in the Wild," in *Proc. International Conference on Computer Vision*, December 2015, doi: 10.1109/ICCV.2015.425.

[64] S. Basak, P. Corcoran, F. Khan, R. Mcdonnell, and M. Schukat, "Learning 3D Head Pose From Synthetic Data: A Semi-Supervised Approach," *IEEE Access*, vol. 9, pp. 37 557–37 573, 2021, doi: 10.1109/ACCESS.2021.3063884.

[65] V. Varkarakis, W. Yao, and P. Corcoran, "Towards End-to-End Neural Face Authentication in the Wild - Quantifying and Compensating for Directional Lighting Effects," *CoRR*, vol. abs/2104.03854, 2021. [Online]. Available: https://arxiv.org/abs/2104.03854

ALAKANANDA MITRA (Student Member, IEEE) received a Bachelor of Science (Honors) in Physics from Presidency College, University of Calcutta in 2001 and a Bachelor of Technology and Master of Technology in Radiophysics and Electronics from Institute of Radiophysics and Electronics, University of Calcutta in 2004 and 2006 respectively. Currently, she is a doctoral student in the research group at Smart Electronics Systems Laboratory (SESL) in the Department of Computer Science and Engineering at University of North Texas, Denton, USA. Along with her course work, she also works as a Teaching Assistant in the department. She has worked as a Project Linked Personnel at Advanced Computing and Microelectronics Unit in Indian Statistical Institute from 2006 to 2007. Her research interests include artificial intelligence, machine learning, deep learning, edge AI, and application of AI/ML approaches in multi-media forensics, smart agriculture, and smart healthcare.



DAN BIGIOI graduated from the National University of Ireland Galway in 2020 with a bachelor's degree in Electronic and Computer Engineering. Upon graduating, he worked as a research assistant at NUIG studying the text to speech and speaker recognition methods under the DAVID (Data-Center Audio/Visual Intelligence on-Device) project. Currently, he is working on his Ph.D. at NUIG, sponsored by D-REAL, the SFI Centre for Research Training in Digitally Enhanced Reality. His research involves studying and implementing novel deep learning-based techniques for Automatic Speech Dubbing and discovering new ways to process multi-modal audio/visual data.

SARAJU P. MOHANTY (Senior Member, IEEE) received the bachelor's degree (Honors) in electrical engineering from the Orissa University of Agriculture and Technology, Bhubaneswar, in 1995, the master's degree in Systems Science and Automation from the Indian Institute of Science, Bengaluru, in 1999, and the Ph.D. degree in Computer Science and Engineering from the University of South Florida, Tampa, in 2003. He is a Professor with the University of North Texas. His research is in "Smart Electronic Systems" which has been funded by National Science Foundations (NSF), Semiconductor Research Corporation (SRC), U.S. Air Force, IUSSTF, and Mission Innovation. He has authored 400 research articles, 4 books, and invented 7 granted/pending patents. His Google Scholar h-index is 44 and i10-index is 185 with 8800 citations. He is a recipient of 14 best paper awards, Fulbright Specialist Award in 2020, IEEE Consumer Electronics Society Outstanding Service Award in 2020, the IEEE-CS-TCVLSI Distinguished Leadership Award in 2018, and the PROSE Award for Best Textbook in Physical Sciences and Mathematics category in 2016. He is widely credited as the designer for the first digital watermarking chip in 2004 and the first low-power digital watermarking chip in 2006. He has delivered 15 keynotes and served on 13 panels at various International Conferences. He has been the Editor-in-Chief of the IEEE Consumer Electronics Magazine during 2016-2021 and serves on the editorial board of multiple journals/transactions.

PETER CORCORAN (Fellow, IEEE) currently holds the Personal Chair in electronic engineering with the College of Science and Engineering, National University of Ireland Galway (NUIG). He was the Co-Founder of several start-up companies, notably FotoNation (currently the Imaging Division, Xperi Corporation). He has more than 600 cited technical publications and patents, more than 120 peer-reviewed journal articles, 160 international conference papers, and a co-inventor on more than 300 granted U.S. patents. He is an IEEE Fellow recognized for his contributions to digital camera technologies, notably in-camera red-eye correction and facial detection. He is also a member of the IEEE Consumer Technology Society for more than 25 years and the Founding Editor of IEEE Consumer Electronics Magazine

ELIAS KOUGIANOS (Senior Member, IEEE) received a BSEE from the University of Patras, Greece in 1985 and an MSEE in 1987, an MS in Physics in 1988 and a Ph.D. in EE in 1997, all from Louisiana State University. From 1988 through 1998 he was with Texas Instruments, Inc., in Houston and Dallas, TX. In 1998 he joined Avant! Corp. (now Synopsys) in Phoenix, AZ as a Senior Applications engineer and in 2000 he joined Cadence Design Systems, Inc., in Dallas, TX as a Senior Architect in Analog/Mixed-Signal Custom IC design. He has been at UNT since 2004. He is a Professor in the Department of Electrical Engineering, at the University of North Texas (UNT), Denton, TX. His research interests are in the area of Analog/Mixed-Signal/RF IC design and simulation and in the development of VLSI architectures for multimedia applications. He is an author of over 140 peer-reviewed journal and conference publications.