SafeAccess: Towards a Dialogue Enabled Access to the Smart Home for the Friends and Families

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Abstract—SafeAccess is an interactive assistive technology solution to enhance the safety and independence of people with disability (i.e., visually impaired and limited mobility). The system output is the classification and identification of a person in front of the door or around the house into groups such as friends/families/caregiver versus intruders/burglars/unknown. This will allow the user to grant/deny remote access to the premises or ability to call emergency services. In this paper, we focus on designing a prototype system and building a robust recognition engine that meets the system criteria and addresses speed, accuracy, deployment and environmental challenges under a wide variety of practical and real-life situations. The premise is assumed to be equipped with cameras placed at strategic locations to capture images and videos. To interact with the system, we implemented a dialog enabled interface to create a personalized profile using face images or video of friend/families/caregiver. To improve the computational efficiency, we apply change detection to filter out frames and use Faster-RCNN to detect the human presence and extract faces using Multitask Cascaded Convolutional Networks (MTCNN). Subsequently, we apply LBP/FaceNet to identify a person and groups by matching extracted faces with the profile. SafeAccess sends identification result to the users with an MMS containing persons name if any match found or as “intruder, scene image and a confidence score between 1 to 10. In addition, the daily, weekly and monthly summarized report of the past incident can be queried from the system. Empirical analysis shows a robust performance with an F-score of 0.97 in identifying friends/families/caregiver versus intruders/unknown.

Index Terms—Assistive technology, face recognition, convolutional neural network, home security

I. INTRODUCTION

In 2013, a study conducted by The Christopher & Dana Reeve Foundation showed that 1 in 50 people are living with some form of paralysis in the USA. Visual impairment is one of the most severe types of disability among six major disabilities (physical disability, visual disability, hearing disability, mental health disabilities, intellectual disability, and learning disability). According to the World Health Organizations estimation, 285 million people are visually impaired around the globe. Among those, 39 million are blind, and 246 million have low vision. A project called Cost of vision’ conducted by Prevent Blindness America (PBA) revealed that the total economic burden of eye disorders and vision loss in the United States in 2013 is 139 billion. The people with vision impairments and limited mobility (paralyzed partially or entirely) often face difficulties interacting with the surrounding environment. The most frustrating impact of vision loss is, it creates dependency on sighted people for navigation, finding objects, reading text/labels, detecting abnormal event and intruders, and so on. Visually impaired people mostly depends on hearing ability to identify a person that is limited to a certain distance. A house can be equipped with smart devices that will allow people to communicate from outdoor. Those systems are convenient for identifying known people with close proximity. However, people want to detect the abnormal activity or intruders silently from remote distance. One of the implied overhead of the existing security system is, it requires continuous monitoring of real-time videos by human observers to detect abnormal activity or intruders. Noah Sulman et al. [1] found in a study that when the number of monitoring displays increases human performance deteriorates. They reported that a human observer missed 20% of the event while monitoring four surveillance display. However, when they increased the number of the display window to nine missing rates rose to 60%

In recent years many research have been conducted on navigation [2], wayfinding [3], text reading [4], barcode reading, currency recognition [5], object recognition [6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17], abnormal activity detection in crowd, fall detection for elderly people, gender identification, behavioral expression detection [18], and so on to assist people with vision impairments. However, developing an assistive solution to identify friends/families/caregiver versus intruders/burglars/unknown and responding to the entrance door from remote did not receive considerable attention from researchers. Hence, we developed SafeAccess; a dialogue enabled-interactive system to assists people with vision impairments and limited mobility in identifying known person versus unknown and opening/closing entrance door for a person of interest. This is a novel system with the following features and contributions: 1) Automated identification of friends/families/caregiver versus intruders/burglars/unknown in the surveillance video. 2) opening/closing entrance door remotely for the person of interest 3) smart door installation 4) utilizing computational & network resources by change detection 5) adding voice over interaction to address accessibility issue 6) detection of face orientation and frontalization of faces
7) automatic detection of lighting condition for day/night scene
8) Neutralizing the effect of contrast & brightness in video streams. In addition to those contributions, we have addressed numerous challenges in system design, development, coding, and integration.

We assumed that people with vision impairments and limited mobility will receive help from sighted people to create Personalized Profile, to install cameras and to set up Smart Door (described in respective sections). The house will be equipped with cameras covering the critical points of a home described in the section “Camera Installations. A raspberry pi connected to the cameras will send video stream when a change is detected (see Change Detection) in the scene to the recognition module. The data transmission between cameras and raspberry pi will be done using intra-home Wi-Fi or wired connection based on coverage area and distance. SafeAccess can be configured to work either in standalone or integrated mode based on computational resources. In standalone mode, face recognition unit (LBP model) resides in raspberry pi and runs with limited features. However, we assumed that a home will have an internet connection and SafeAccess will run in integrated mode. The recognition module will process the video feeds to detect the person. If a person is detected, then it will search for faces and match the faces with the personal profile. The system will broadcast the detection & recognition outcome to the feedback unit. The feedback unit will send the notification via email, text, MMS and will call the listed users based on their preference. The user will be able to configure the notification frequency for an event. The system will send the scene image with notification message for further investigation and allow users to open/close the entrance door remotely or call the emergency services if they find intruders/burglars. Since MMS contains scene image, it will help to prevent fooling the system by holding a printed image of friend & families in front of the camera. Because human eyes are good at differentiating printed image vs actual image. It might be challenging for people with vision impairments to analyze those MMS, so SafeAccess will allow them to make a phone call to the friends standing at the entrance. The system will record the video streams based on user preferences and will allow them to query summarized history.

II. RELATED WORKS

Identifying friends/families and responding to the door is a two steps process. First, we need to detect & recognize the person from the surveillance video and then opening/closing the entrance door. To detect a person in surveillance video, most of the state-of-the-art system first finds objects from motion information and then classify that object as human. The classification of the detected object is performed based on any of three approaches: shape-based method, motion-based method or texture-based method. In the shape-based method, shape information such as point, blob, and boxes of moving region are extracted to classify objects using pattern recognition and computer vision technique. Local Binary Pattern (LBP) is a widely used technique in texture-based method to detect human. The other popular texture-based human detection method is Histogram of Gradient (HOG). There is a comprehensive discussion of those methods in this review [20].

The recent advancement in Machine Learning and Computer Vision, especially Convolutional Neural Network (CNN) has made the object and person detection task robust and efficient compared to the last decade. The computational complexity for training a model has reduced in a great extent with the rapid improvement in high-performance computing (HPC) and GPU. Moreover, the public image repository such as ImageNet, PASCALVOC played an important role in the success of visual recognition. Alex Krizhevsky et al. [21] has done ground-breaking work in object recognition using CNN from a large dataset. They trained a deep CNN with 1.2 million images from 1000 different classes with huge optimization in the parameters. The training time was reduced using Rectified Linear Unit. Krizhevsky and his colleague were more focused on building generalized object recognition model. This approach does not provide information about object location. Dumitru Erhan et al. reported a deep neural network based scalable object recognition model [22] which identifies and localize objects with a probable bounding box. Girshick et al. proposed a method R-CNN [23]: Region with CNN features, to localize objects. It shows considerable improvement from contemporary works. They achieved tremendous success by replacing HOG features with CNN features in lower layers. Using selective search algorithm, they generate proposal of bounding boxes which are then passed to AlexNet [21] to get the labels for each bounding box. They used linear regression to localize objects more precisely. However, their approach has two major drawbacks. First, Extracting CNN features and forward pass for each region proposal is computationally very expensive. Second, three models are trained separately for CNN feature extraction, classification and generating tighter bounding box. This problem has been addressed in their later work called Fast-RCNN [24]. In R-CNN, the proposed regions have a significant overlap which caused to perform the repetitive computation. The redundant computation was eliminated by sharing forward passes using Region of Interest (RoIPool). Moreover, they combined three models in one network. R-CNN and Fast-RCNN use a selective search algorithm to generate object proposal which is very slow. Shaoqing Ren et al. presented a near cost free architecture called Faster-RCNN [25] to generate region proposals. They reused CNN feature map for region proposals instead of running selective search separately. Kaiming He et al. presented a technique called mask-RCNN [26] which advanced localization task to pixels level. Sermanet et al. [27] presented an integrated system called overfeat, where a multiscale and sliding window technique was used with ConvNet to classify, localize and detect items. They allowed five guesses to identify the correct label and position of an object since an image might be cluttered with other objects. Yi Sun et al. built “DeepID3” [28], a face recognition model from stacked convolution and inception layers.
III. SYSTEM DESIGN AND DEVELOPMENT

Designing any assistive solution considering “System Thinking”, “Design Thinking” and “Assistive Thinking” is important because it helps to understand the complexity of a problem and to solve it effectively. System thinking is a set of practices within a framework that emphasizes considering the component of systems as a whole, rather than in isolation. Thinking systematically also requires several shifts in perception, which lead in turn to different ways to teach, and different ways to organize a system. Design thinking is applying designer’s sensibility and methods to solve problems, more specifically, its a methodology for innovation and enablement. During the development of the system, in every phase and aspect, we tried to minimize the user’s effort by reducing the system’s complexity. There are some useful tips we have followed to design SafeAccess from this technical guidance [29] to address the accessibility issue. We also considered the distribution of targeted users and their ability to receive the service. Most of the assistive solutions fall short of addressing many accessibility and usability issues. “Design for Usability” is entirely different for people with low vision than sighted one. Javier and colleague [30] introduce a concept called Low Vision Mobile App Portal, which describes how to access mobile apps those are designed for visually impaired people. SafeAccess has been compartmentalized into six modules: 1) Profile Creation module 2) Camera installation Module, 3) Smart Door setup module 4) Recognition Engine 5) Feedback module. We designed and developed each component individually, and then we integrated all pieces by applying the learnings from System Thinking. The architecture of SafeAccess is shown in figure 1 and each module has been described in their respective sections. A Raspberry Pi connected to the cameras placed at different points around the house is responsible for capturing frames and transmitting it to the recognition module. Recognition engine detects and recognizes the person. Feedback module sends the recognition outcome to users and users responds to the door using SafeAccess app.

A. Profile Creation module

In order to identify a person, the recognition model needs to be trained with face images of friends/families/caregiver from personalized profile. The personalized profile will contain demographic information (Name, Email, Contact, Address) and face images with different expression (Joy, Sad, Surprise, Fear, Contempt, Disgust). SafeAccess app will enable user to collect images from camera preview/photo gallery/video clip. We have included four utility features to create a personal profile: 1) Add Person: This option is to include a new person with demographic information and images from different view 2) Add views: using this option new picture of a person can be added to the profile. Users are suggested to add multiple views of a face in the training sample so that the system can recognize a person with various poses and view angles in natural settings. 3) Delete person: this option can be used to delete all information about a person from the profile 4) Read out Summary: This option will be used to know the history of abnormal activity or appearance of unknown persons especially when a user misses any feedback.

B. Camera Installation Module

There are many factors need to be considered before purchasing and installing cameras; 1) what type of cameras to choose: we need to check the durability of the camera considering the weather and temperature of the surroundings throughout the year, image quality, data transmission rate, the field of view angle (FOV), wireless versus wired. Camera unit must be protected from rain and extreme weather. The images with high resolution are better for image analysis and provide robust recognition outcomes, but transmission latency is high. We need to draw a trade-off between camera resolution and data transmission latency. Wireless cameras are easy to install but when the distance between the camera and Wi-Fi hub increases the signal strength decreases. So, we need to choose a wireless versus wired camera based on coverage area. 2) How many cameras are required: the number of cameras required to protect a home depends on the size of the house, coverage area, and indoor versus outdoor layout. 3) Where to place: identifying critical places to install cameras is essential because monitoring the entire area is expensive. In 2005, law enforcement agency reported more than 2 million burglary offenses in the USA [31]. The survey revealed that 81% burglar entered home through the first floor (34% burglar chose the front door, 23% first-floor window, 22% back door, and 2% storage area). Remaining 9% burglar selected garage, 4% basement, 4% unlocked entrance, and 2% anywhere on the second floor to enter inside in the house. The statistics show the first floor is more vulnerable to the burglars compare to any other point of a house. Considering theft and burglary statistics camera can be installed at the front door, back door, off-Street windows, driveways, porches, and stairways 4) what is the optimal view angle: How wide or narrow monitoring view we want depends on the field of view angle (FOV). If the FOV of a camera is large, it can capture wide view but the objects in those views will be very small. If the FOV is small, it can capture small area, but objects in those views will be large. 5) and lastly, How much it will cost.

We assumed that a camera will be installed at the entrance door at a height between 6-7 ft in addition to other locations. It will help to acquire frontalized faces of the entering person. There is a chance that people might tamper the camera if we
put in such a low height. However, there are some hidden
cameras available in the market those can be used just for
entrance doors. The images captured from a camera located
at the top- corner of a building usually has a tilted view and
most of the time it is difficult to align those faces/images.
The state-of-art face alignment algorithm can frontalize faces with
a limited angle.

C. Smart Door setup module

A safe and secure door is one of the most important
parts of a smart home. The smart door can be opened and
closed without requiring physical keys. There is numerous
commercial product to build a smart door such as August
Smart Lock[32], Schlage Sense[33], ZigBee Lock[34] etc. The available features provided by those commercial
systems are: 1) allowing users to control(open/close) door from
smartphone, web or desktop app 2) logging history of who is
entering and leaving home 3) setting custom privilege to allow
friends and family to enter and leave home 4) geofencing:
setting a perimeter around the house on mobile app with
location services, when users leave that perimeter door will
be automatically locked. 5) Sending activity notifications when
someone tries to tamper the lock and enter forcefully. Most
of the commercial system use Bluetooth and Wifi-enabled
lock to control the door. Bluetooth allows controlling door
from close proximity while wifi enables to control door from
anywhere if it is connected to the internet. In our experiment,
we used Sonoff SV Wifi enabled-switch to control Solenoid
door Lock. The user will send the command(open/close door)
from the SafeAccess app. The app will send an instruction
to Sonoff switch, and it will lock or unlock the door. The
underlying architecture of the smart door is shown in Figure
2 When there is no power in solenoid lock door will be
closed that’s how we can save the power consumption. When
user will send the command to unlock door Sonoff switch
turn on the lock and door will be open. The door will be
closed automatically after a certain time elapsed. This time
interval can be set according to users preferences. The power
requirement for Sonoff varied from 5V to 250V. It supports
a various generation of Wifi and frequency range from 2.4
GHz to 433MHz. Sonoff requires custom firmware to prevent
potentials vulnerability from hackers and to set users specific
network configuration. The custom firmware will enable to set
user-defined wifi SSID(Service Set Identifier) and password.
There is several firmware available but ESP Easy[35] and
Tasmota[36] are widely used. In order to install custom
firmware, we need a 0.1-inch straight pin header, USB 2.0
to TTL, solder, Arduino IDE and firmware code downloaded.
Sonoff can be configured and added to the home internet router
to make it accessible from anywhere.

D. Recognition Engine

The Recognition module runs on a remote server and
consists of two components: 1) Person Detector 2) Person
Recognizer. The reason for including a person detection model
is to notify users about human presence even if there is no face
found specially when front view of a person is not visible
to the cameras. A convolutional network-based model, Faster
R-CNN[25] has been trained on the dataset collected from
PASCAL VOC 2012 and ImageNet. Faster R-CNN introduced
Region Proposal Network (RPN) with a massive improve-
ment in computational complexity to find object proposals by
sharing convolutional layers. They reused feature map which
already calculated in the forward pass of R-CNN. RPN is a
fully connected convolutional layer which runs on top of CNN
convolutional layers. RPN slides a small window over the
CNN feature map and outputs k potential bounding boxes and
associated scores indicating how likely that box will contain
an object. The class labels for those proposed bounding boxes
are obtained from Fast R-CNN. An image might have multiple
bounding boxes with various objects and persons. In order
to recognize a person, first, we need to make sure there is
a face in that cropped bounding box. Figure 2 shows some
bounding boxes with the frontal/non-frontal faces. We used
Multitask Cascaded Convolutional Networks (MTCNN)[37]
face detector to find faces in those bounding boxes. Once the
face is found then it is sent to person recognizer model to
obtain a person name. We analyzed the recognition accuracy
using four methods: Eigenface[38], FisherFace[38], Local
Binary Pattern (LBP)[39], and FaceNet[40]. EigenFace is
a Principal Component Analysis based model which projects
the higher dimensional data into lower dimensional space. The
drawbacks of this methods is that the directions with
the highest variance and very error prone to noise. Some
discriminative information may be lost because it does not
consider classes. Fisherface is Linear Discriminative Analysis
(LDA) based method which performs class-specific dimension
reductions. It maximizes between class ratios and minimizes
inner class ratio. Fisherface works fine with the constrained
environment and had sufficient training sample. However, real-
world scenarios are not perfect and have a limited option to
control geometric and photometric information. LBP works reasonably well even with a very small number of training samples. LBP extracts features such as textures & shapes from the small local region of an image and has low dimension inherently. It calculates a binary code for a central pixel based on the intensity of surrounding pixels by applying a threshold. Then it calculates a histogram of those patterns and uses nearest neighbor classifiers to find a class label. The deep neural network has made face recognition task more robust. Parkhi et al. presented “Deep face recognition” [41]: a Convolutional neural network based model to recognize faces. Florian et al. presented “FaceNet” [40], a CNN based unified embedding for face recognition. The major drawback of deep neural network based model is that it takes a long time to train the model for low form factors device like raspberry pi. So, if the personal profile gets changed by addition or deletion of any person or views images then retraining those model is very burdensome. we have used LBP as a primary face recognition model for Raspberry Pi in standalone mode and FaceNet for devices with high computational resources in integrated mode.

E. Feedback Module

Feedback module is responsible for sending notifications to the users for identified activities. Designing an effective feedback system for people with disabilities is very challenging because very few of them know how to use accessibility features such as TalkBack, Siri and other voice over utilities offered by smartphones. Considering the technical adaptability of the users, we have included three types of feedback modes: MMS, email, and phone call. Those feedback mode can be set based on user preference. We are using SMTP (Simple Mail Transfer Protocol) server to send those SMS & MMS to the users via their phone operator. To make a phone call, we are using Twilio [42] 3rd party service which will cost $0.013/minute. The additional task of the feedback module is storing the history of the activities in the persistent storage. We have used a MySQL database to store personal profile and event history.

IV. SYSTEMS NOVELTY FEATURES AND CHALLENGES

The robust detection and recognition of person/intruder from surveillance video are more challenging than detecting arbitrary objects for several factors. First of all, the lighting conditions of outdoor environment changes with the time of a day and weather which sometimes makes the surveillance videos difficult to read and understand. The other factors are background clutter, facial appearance (pose, hairstyle, makeup, mustache, beard, aging, and expression), position, resolution, and field of view of a camera, etc. To overcome some those challenges, we have included following novelty features in SafeAccess.

A. Change Detection

Although nowadays computational resources are easily accessible, the fast processing unit like GPU or HPC is still expensive. Considering the cost-effectiveness and network utilization, we only transmit, process and store video frames that has an activity or a change has been detected. The captured camera stream will not have any activity unless an event occurs such as a person enters into the monitoring area or any natural events like rain, storm changes the scene. In order to find a frame with activity, we perform change detection by subtracting consecutive frames. In figure 4 we have shown the outcome of change detection (right) from two frames (left, middle). In the middle frame an event, shooting is happening. The outcome of the change detection can be affected by the changes, in contrast, brightness, and unwanted artifacts. Using gamma correction we neutralized the effect of the brightness on change detection. The other unwanted artifact were suppressed by applying two level of thresholding; 1) Pixel level thresholding: each pixel on the subtracted frame is compared with a threshold if the pixel is above the threshold then assigning a value 255. We examined the robustness of change detection with two types of pixel level threshold: a) binary or global user-defined threshold b) adaptive threshold with Gaussian window. The only difference between adaptive and binary thresholding is that one learns the threshold from neighborhood pixels, and other has global predefined threshold. We found from the experiments binary thresholding provides robust change detection compare to adaptive. Adaptive thresholding more sensitive to noise, contrast & brightness. Figure 5 shows a comparison of two approaches. 2) Global thresholding: we applied a global threshold on summed pixels value for the entire subtracted frame on top of pixel level threshold. We assumed for robust identification face size would be at least 32X32. So total changes in pixels values would be at least 32*32*255=261120 in two successive frames when a person appears in the scene. If we set this threshold to find activates the model becomes very conservative hence generates less false positive (high precision 0.991) and high false negative (low recall 0.94). Provided the context we are dealing with; a high recall is more important to us compare to high precision since we don’t want to miss any activity. We analyzed the reason for generating high false negative and found that there some frames where the spread of the changes exceeds the region 32X32, and pixel difference is zero inside that region due to the first level threshold. However, when we reduced the threshold to less than 100000 model becomes very liberal and produces lots of false positive. So we considered 100000 as the second level threshold.
B. Automatic detection of lighting condition (night vision)

The lighting condition is an important factor for analyzing an image for face detection and recognition. The video streams captured in the night or in extreme weather might not have enough light. In the alpha version, we implemented a computationally simple technique to detect and notify lighting condition by calculating intensity histogram. In figure 6, a well-lighted (a) and a dark image (c) is shown with their intensity histogram. In the well-lighted image histogram (b), pixels are distributed all over the bins. However, in dark image histogram (d) pixels distributions are skewed and resides in the first few bins. So, if the first few bins in intensity histogram contain 70% (experimented threshold) of the image pixels, then we notify the lighting condition is not enough. In the beta version, the user will be able to set up an automated lighting system to handle poor lighting conditions.

C. Face frontalization

Face frontalization is a challenging problem for any face recognition based systems because face might have various poses and orientations. Non-frontal and out of plane face is hard to recognize for any computer vision based engine. To deal with this problem, we have included faces from the different views (a sample is shown in figure 7) in the training data. However, it is very burdensome to include faces in the profile covering all possible orientations and pose. Face frontalization or alignment technique will increase the recognition performance. The idea of face frontalization is making the eyes, lips, and nose are centered as much as possible. In order to achieve that, first, we identified faces that need to be frontalized because if we apply frontalization on faces that are already aligned it may change facial properties. We have presented a novel and straightforward approach to detect non-frontal and out of plane faces by finding 68 facial landmark point such as chin, eyes, and eyebrows (shown in figure 8 left) using the technique presented by Vahid Kazemi [38]. The face orientation is detected by measuring two parameters \( \alpha \), \( \beta \); rotation about the x-axis and z-axis respectively. The parameter \( \beta \) is calculated from the slope of the connecting line between the centroid of left & right eyes. The parameter \( \alpha \) is calculated by forming a triangle with points A=0, C=33, B=16 (shown Figure 8 (left), points are marked with a circle). Experimentally we have found a face with no tilt forms a triangle where angle ACB is approximately 120°. If the angle is above 120° the face is tilted up and if it is below 120° then face is tilted down. Some sample faces with different pose & tilt angle are shown in Figure 9 (a,b,c). The angle between AC & BC, ABC, has been calculated using equation 1

\[
\theta = \tan^{-1} \frac{m_1 - m_2}{1 + m_1 \times m_2}
\]

where \( m_1 \) & \( m_2 \) are the slopes of line AC & BC respectively. Now, based on \( \alpha \) & \( \beta \), the system decides whether a face requires frontalization or not and apply “Effective face frontalization in unconstrained images” techniques presented by Hassner et al. [42] for faces with extreme postures only. Figure 9(d & e) shows a sample face with extreme posture and corresponding frontalization outcome. The average recognition accuracy after applying face frontalization on faces with large tilt and skewd orientation is 23% while systems fails completely to identify those faces without frontalization.

D. Remote control of Smart Door

SafeAccess will allow the users to see and verify recognized person and remotely open the door. The user will be able to open the door from anywhere for their family & friends as long
as they have an internet connection. If any family members forget to take keys with them this option will allow them to enter home.

E. Finding Supported Camera

There are numerous camera in the current market with a wide variety of resolutions. So its hard to choose a camera with proper resolution for capturing video streams which will provide robust recognition. In order to make the camera selection task easy we analyzed the effect of face-image resolutions on final recognition by downsampling detected face to 20X20, 32X32, 64X64, 96X96, 150X150, 300X300 and resizing it to 400x400 to match with training dataset. A sample is shown in figure 10(a), where the detected face has been downsampled to 32x32. When we resized the image to 400x400 (shown figure 10(b)) the resolution, especially the spatial resolution becomes very poor even if the total number of pixels increased. From the experiments, we have found that the average F-measure of recognition with LBP model for those face resolutions are 0.92 0.95, 0.96, 0.96, and 0.96 respectively. The experiment shows recognition outcome is robust with medium & high face resolutions. The screen resolutions of the cameras that we used are 1280 x 720 (camera 1) and 1920X720 (camera 2). However, when downsampled the detected faces too low, to 20X20 (shown figure 10(c)) recognition outcome dropped. So any camera even with 5 to 10 times low resolution than camera 1 & camera 2 respectively can be used. The experiment has been conducted for various face resolutions (figure 10(e), width & height in X & Y axis).

![Fig. 10. Effect of face resolution on final recognition](image)

V. MODEL TRAINING

The person detection model, Faster-RCNN has been trained with PASCALVOC 2012 dataset which contains 11,530 images. The size of the input image is 600x600. NVIDIA GTX 1080 GPU with 2560 CUDA core has been used to train the model for 300 iterations with batch size 600. It took 74 hours to train the ResNet50. The person recognizer model was trained with 180 images captured from 16 subjects.

VI. EXPERIMENT AND RESULTS

SafeAccess has been evaluated with real-time video streams collected using Logitech C270 HD webcam placed in-front of the door. We recorded each video session so that we can evaluate different recognition model with identical settings. Those sessions were captured at a different time point of a day to check how the system performs at different lighting conditions. The average F-measure of identifying friends/families using EigenFace, FisherFace, LBP, and FaceNet are 0.94, 0.95, 0.96 and 0.97 respectively. Among the four models, we have selected LBP and FaceNet because of their robustness. We found some scenarios where SafeAccess failed to identify persons when faces were out of the plane with a large tilt.

VII. CONCLUSION

We have presented SafeAccess, a smartphone based integrated solution to help people with disability to live independently and with dignity. Here I will quote comments from Apple senior manager, Sarah Herrlinger: For some people, doing something like turning on your lights or opening a blind or changing your thermostat might be seen as a convenience, but for others, that represents empowerment, and independence, and dignity [43]. SafeAccess monitors who is entering & leaving home and identify friends/families/caregiver versus intruders/unknown. In the alpha version, we have built a prototype for a smart house, developed an integrated person recognition system by addressing several accessibility, usability & technical challenges. In beta version, we will 1) incorporate more efficient techniques to handle out of plane & non-frontal faces 2) develop an algorithm to remove/neutralize the effect of rain in the video streams. 3) add servo motor to adjust camera mount to provide the best possible coverage when any activity found 4) generate a description on facial appearance, whether the detected person has the beard, mustache or eyeglasses, etc.

REFERENCES

[1] N. Sulman, T. Sanocki, D. Goldgof, and R. Kasturi, “How effective is human video surveillance performance?” in Pattern Recognition, 2008. ICPR 2008. 19th International Conference on. IEEE, 2008, pp. 1–3.

[2] G. Kao, P. Probert, and D. Lee, “Object recognition from fm sonar; an assistive device for blind and visually-impaired people,” in AAAI Fall Symposium, 1996.

[3] R. Gude, M. Østerby, and S. Soltveit, “Blind navigation and object recognition,” Laboratory for Computational Stochastics, University of Aarhus, Denmark, 2013.

[4] “ocr: Mobile OCR, Face and Object recognition for the Blind.” [Online; accessed 05-February-2014].

[5] “LookTel Recognizer.” [Online; accessed 12-February-2014].

[6] D. Mapelli and M. Behrmann, “The role of color in object recognition: Evidence from visual agnosia,” Neurorcase, vol. 3, no. 4, pp. 237–247, 1997.

[7] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, “Orb: an efficient alternative to sift or surf,” in Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011, pp. 2564–2571.

[8] S. Alam, I. Anam, and M. Yeasin, “O’map: An assistive solution for identifying and localizing objects in a semi-structured environment,” 2015.

[9] B. Schauerte, M. Martinez, A. Constantinescu, and R. Stiefelhagen, An assistive vision system for the blind that helps find lost things. Springer, 2012.
[10] C. Yi, R. W. Flores, R. Chincha, and Y. Tian, “Finding objects for assisting blind people,” *Network Modeling Analysis in Health Informatics and Bioinformatics*, vol. 2, no. 2, pp. 71–79, 2013.

[11] R. Chincha and Y. Tian, “Finding objects for blind people based on surf features,” in *Bioinformatics and Biomedicine Workshops (BIBM), 2011 IEEE International Conference on*. IEEE, 2011, pp. 526–527.

[12] “FindIT,” [http://www.ambitiousideas.com/findlostkeys.html](http://www.ambitiousideas.com/findlostkeys.html) [Online; accessed 18-February-2014].

[13] “KeyRinger,” [http://www.keyringer.com/](http://www.keyringer.com/) [Online; accessed 16-February-2014].

[14] “Sonic Key Finder,” [http://www.keyringer.com/sonic-key-finder.html](http://www.keyringer.com/sonic-key-finder.html) [Online; accessed 16-February-2014].

[15] “FindOne,” [http://www.findonefindall.com/](http://www.findonefindall.com/) [Online; accessed 17-February-2014].

[16] J. P. Bigham, C. Jayant, A. Miller, B. White, and T. Yeh, “Vizwiz:: Locateit-enabling blind people to locate objects in their environment,” in *Computer Vision and Pattern Recognition Workshops (CVRP), 2010 IEEE Computer Society Conference on*. IEEE, 2010, pp. 65–72.

[17] “Blind and Visually Impaired Camera,” [http://www.taptapseeapp.com](http://www.taptapseeapp.com) [Online; accessed 15-February-2014].

[18] A. Anam, S. Alam, and M. Yeasin, “Expression: a google glass based assistive solution for social signal processing,” in *Proceedings of the 16th international ACM SIGACCESS conference on Computers & accessibility*. ACM, 2014, pp. 295–296.

[19] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[20] M. Paul, S. M. Haque, and S. Chakraborty, “Human detection in surveillance videos and its applications- a review,” *EURASIP Journal on Advances in Signal Processing*, vol. 2013, no. 1, p. 176, 2013.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

[22] D. Erhan, C. Szegedy, A. Toshev, and D. Anguelov, “Scalable object detection using deep neural networks,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 2147–2154.

[23] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 580–587.

[24] R. Girshick, “Fast r-cnn,” in *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 1440–1448.

[25] 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*, 2015, pp. 91–99.

[26] K. He, G. Gkioxari, P. Dollár, and R. Girshick, “Mask r-cnn,” in *Computer Vision (ICCV), 2017 IEEE International Conference on*. IEEE, 2017, pp. 2980–2988.

[27] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun, “Overfeat: Integrated recognition, localization and detection using convolutional networks,” *arXiv preprint arXiv:1312.6229*, 2013.

[28] Y. Sun, D. Liang, X. Wang, and X. Tang, “Deepid3: Face recognition with very deep neural networks,” *arXiv preprint arXiv:1502.00873*, 2015.

[29] “Best Practices,” [www.youtube.com/watch?v=1by5l7c5Vz4](https://www.youtube.com/watch?v=1by5l7c5Vz4) [Online; accessed 15-December-2018].

[30] J. Sanchez and J. Selva Roca de Togores, “Designing mobile apps for visually impaired and blind users,” in *ACHI 2012, The Fifth International Conference on Advances in Computer-Human Interactions*, 2012, pp. 47–52.

[31] “Camera Installations,” [https://www.nachi.org/burglar-resistant.htm](https://www.nachi.org/burglar-resistant.htm) [Online; accessed 01-January-2018].

[32] “Door lock,” [http://august.com/](http://august.com/) [Online; accessed 15-January-2018].

[33] “Door lock,” [https://www.schlage.com](https://www.schlage.com) [Online; accessed 20-January-2018].

[34] Y. T. Park, P. Sthapit, and J.-Y. Pyun, “Smart digital door lock for the home automation,” in *TENCON 2009-2009 IEEE Region 10 Conference*. IEEE, 2009, pp. 1–6.

[35] “Easy ESP,” [https://en.wikipedia.org/wiki/ESP_Easy](https://en.wikipedia.org/wiki/ESP_Easy) [Online; accessed 15-January-2018].

[36] “Tasmota,” [https://github.com/arendst/Sonoff-Tasmota/wiki](https://github.com/arendst/Sonoff-Tasmota/wiki) [Online; accessed 20-January-2018].

[37] 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.

[38] M. A. Turk and A. P. Pentland, “Face recognition using eigenfaces,” in *Computer Vision and Pattern Recognition, 1991. Proceedings CVPR'91., IEEE Computer Society Conference on*. IEEE, 1991, pp. 586–591.

[39] T. Ahonen, A. Hadid, and M. Pietikäinen, “Face recognition with local binary patterns,” in *European conference on computer vision*. Springer, 2004, pp. 469–481.

[40] F. Schroff, D. Kalenichenko, and J. Philbin, “Facenet: A unified embedding for face recognition and clustering,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 815–823.

[41] O. M. Parkhi, A. Vedaldi, A. Zisserman et al., “Deep face recognition,” in *BMVC*, vol. 1, no. 3, 2015, p. 6.

[42] “Twilio,” [https://www.twilio.com/](https://www.twilio.com/) [Online; accessed 20-March-2017].

[43] “Smart Home Empowers people with disability,” [https://www.nbcnews.com/tech/tech-news/how-smart-home-empowers-people-disabilities-n756731](https://www.nbcnews.com/tech/tech-news/how-smart-home-empowers-people-disabilities-n756731).
[Online; accessed 10-December-2017].