Face Recognition for Newborns: A Preliminary Study

Samarth Bharadwaj, Himanshu S. Bhatt, Richa Singh, Mayank Vatsa and Sanjay K. Singh

Abstract— **Newborn swapping and abduction is a global problem and traditional approaches such as ID bracelets and footprinting do not provide the required level of security. This paper introduces the concept of using face recognition for identifying newborns and presents an automatic face recognition algorithm. The proposed multiresolution algorithm extracts Speeded up robust features and local binary patterns from different levels of Gaussian pyramid. The feature descriptors obtained at each Gaussian level are combined using weighted sum rule. On a newborn face database of 34 babies, the proposed algorithm yields rank-1 identification accuracy of 86.9%.**

I. INTRODUCTION

Swapping of newborn babies is a challenge that is faced by hospitals across the world. In United States, several studies have reported that every year around 1,00,000 - 5,00,000 newborn babies are switched by mistake. Apart from accidental switching, there are instances of abducting babies and illegal adoption [1]. According to the National Center for Missing and Exploited Children, 270 cases of newborn/infant abduction have been reported in the United States from year 1983-2010 [2]. Another study performed in United States by Gray *et al.* concluded that, in the 34 newborns that are admitted to a neonatal intensive care unit at any given day, there is 50% chance of incorrect identification [3]. To ensure that babies are correctly recognized, hospitals have devised several rules. Though ID bracelets are put on babies hands/legs right after birth, this has not been able to prevent swapping of the babies. It is important to note that these are the number of cases that have been reported, there may be many more that are undeclared or the parents and the children never come to know about it.

In medical science, different methods have been explored to identify newborns. Deoxyribonucleic Acid (DNA) typing and Human Leukocyte Antigen (HLA) typing are very efficient and accurate methods for verifying the identity of babies. Due to the amount of time it takes to process a DNA or HLA sample and the cost associated with it, these methods for verification are not feasible for every newborn. Another method, that hospitals are following and is recommended by the Federal Bureau of Investigation [4], is foot and finger printing of the child and mother. A survey reported that 90% of the hospitals in United States perform foot printing of the babies within 2 hours of their birth. There is a *newborn identification form* on which footprint of the child and fingerprint of the mother are collected. The prints are generally collected using ink based methods and then printed on the identification form.

Researchers from both medical and computer science have studied the applicability and reliability of using footprints for newborn identification. Shepard *et al.* presented the analysis of footprints on 51 newborns. The footprints were examined by fingerprint experts of the California State's Department of Justice [5]. Using the footprints, experts were able to identify only 10 babies. Similar results were reported by Pela *et al.* where the analysis was conducted on 1917 foot prints collected by trained personnels of a hospital in Brazil. None of the images provided information sufficient to perform accurate identification [6]. These studies concluded that with the state-of-art capture techniques, it is difficult to use footprint for identifying newborns. Based on these studies, the American Academy of Pediatrics and the American College of Obstetricians and Gynecologists stated that *individual hospitals may want to continue the practice of foot printing or fingerprinting, but universal use of this practice is no longer recommended.*

After footprint, researchers explored the applicability of other biometric modalities such as fingerprint, palm print and ear for verifying the identity of newborn babies. Although fingerprint and palm print recognition are well established modalities to recognize adults (over the age of 5 years), they did not achieve good results in identifying newborns. Weingaertner *et al.* developed a new high resolution sensor for capturing the foot and palm prints of babies[1] [7]. Two images of 106 newborns were collected: one within 24 hours of birth and another at around 48 hours. Fingerprint experts examined the data and the identification accuracy of 67.7% and 83% were obtained using foot prints and palm prints respectively. However, multiple studies have quoted that capturing finger/palm/footprint of newborns is very challenging as it is difficult to hold their hands and legs still. Fields *et al.* have studied the feasibility of ear recognition on a database of 206 newborns [8]. They manually analyzed the samples and concluded that visually ears can be used to distinguish between two children. In all the methods for identifying newborns, no research has evaluated the performance of automatic identification/verification.

Another biometric modalities that have been extensively studied for adults are face [9] and iris [10] recognition. Although iris recognition for adults yields very high accuracy [10], for newborns, it is very difficult to capture iris patterns. To the best of our information, automatic face recognition

S. Bharadwaj, H.S. Bhatt, R. Singh, M. Vatsa are with IIIT-Delhi, India {samarthb, himanshub, rsingh, mayank}@iiitd.ac.in

S.K. Singh is with Department of Computer Science and Engineering, IT-BHU, India sks.cse@itbhu.ac.in

[1]The terms newborns, babies and infants are used interchangeably.

has not been studied for newborns. One reason for this may be the notion that newborns look so alike to untrained adults that it is difficult to differentiate between them using face biometric. This has also been shown experimentally that individuals who have less exposure to non-adult faces are unable to recognize newborns efficiently [11].

It is our assertion that face recognition can be a friendly and cost effective solution for identifying newborns if the performance of automatic matching algorithms is satisfactory. In this research, we have studied the applicability and performance of face recognition to avoid baby switching or for identifying abducted infants. Specifically, we propose a face recognition framework that can be used for recognizing newborns. To evaluate the performance of the proposed algorithm, we have prepared a database of 34 newborns. Experimental results show promise towards using face recognition to avoid swapping and abduction of newborns.

The next section presents the challenges in recognizing newborns using face biometrics. Section III describes the proposed algorithm for recognizing newborns followed by experimental results in IV.

II. Challenges of Face Recognition in Newborns

Face recognition is a long studied problem and several challenges have been identified by the researchers including pose, expression, illumination, aging, and disguise. With newborns, the challenges of aging and disguise are not manifested. However, pose and expression are two important covariates. Since it is difficult to make the newborns sit still and give good frontal images with neutral expression, they can be considered as uncooperative users of face recognition. They may also exhibit different poses and expressions, especially if they become uncomfortable while photographing. Some of these expressions that affect the performance of face recognition are shown in Fig. 1. Further excessive movement can cause motion blur in the images. Another challenge is recognizing twins. Once twins grow up, they may develop differentiating looks but newly born twins are extremely similar. Fig. 2(a) shows images of twins at different age and Fig. 2(b) shows image of a pair of twins present in the newborn face database.

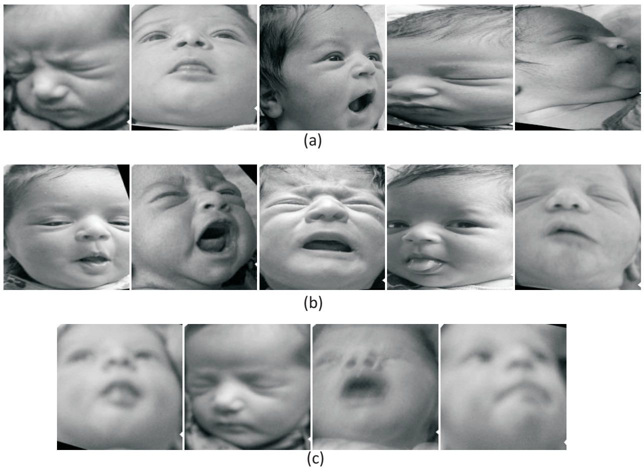

Fig. 1. Some challenging images from the Newborn face database.

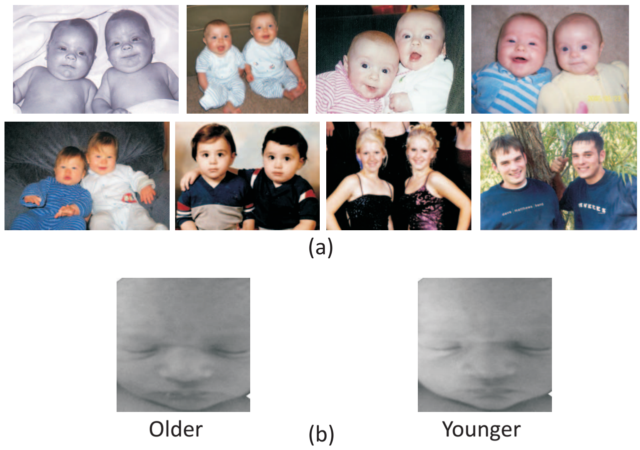

Fig. 2. Sample images of twins. (a) Images taken from *http://www.twinsrealm.com/othrpics.htm* and (b) Images from the Newborn face database.

III. Facial Feature Extraction and Matching

The proposed feature extraction algorithm is motivated by the observation that newborn's have rich skin texture and distinct facial features. Further, it is difficult to restrict pose and expression variations of babies, implying that holistic face recognition algorithms may not yields good results. On the other hand, local feature based algorithm may provide good results. The hypothesis is that for babies, information content present in the image changes with expression variations. To efficiently extract and encode this information, local feature based algorithms must be utilized. The features used in this work are Speeded up Robust Features (SURF) [12] and Local Binary Patterns (LBP) [13]. A brief description of SURF and LBP descriptors is provided below followed by the proposed algorithm in Section III-B.

A. SURF and LBP based Feature Extraction

Speeded Up Robust Features: SURF is a scale and rotation invariant descriptor [12]. It generates a compact representation of the image based on spatial distribution of gradient information within the interest point neighborhood. The interest points found using scale space representation are detected at different scales. Scale space is usually implemented as image pyramids obtained by Gaussian smoothing and sub-sampling. In SURF, scale space is explored by upscaling the integral image and combining with a fast Hessian matrix. Interest points are localized by non-maximum suppression in a $3 \times 3 \times 3$ neighborhood. Once the interest points are detected, gradient information is assimilated from the neighboring sample points as Haar wavelet response in x and y direction. Haar wavelet response is calculated within a circular region of radius $6 \times s$, where s is the scale at which the key point has been detected. Every interest point is assigned an orientation based on the Haar wavelet responses in a sliding oxidation window around the circle.

Descriptor: SURF descriptor is calculated by sampling a square region around the interest point along the orientation of the interest point. Square region is further divided into 4×4 sub-regions and for each sub-region Haar wavelet responses for 5×5 evenly sampled points are calculated. Wavelets responses in x-direction and y-direction are summed over the sub-region and $\sum d_x$ and $\sum d_y$ are computed. Absolute values of responses in x-direction and y-direction, $\sum |d_x|$ and $\sum |d_y|$, are also incorporated in the descriptor to bring information about the polarity of change in intensities value. At each sub-region, a vector $S = [\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|]$ is calculated. This yields an $m \times m \times 4$ descriptor for the key point that captures the intensity structure around the key point region (m is generally 4).

Local Binary Patterns: LBP descriptor is a widely used texture operator because of its robustness to gray level changes and high computational efficiency [13], [14]. The basic LBP descriptor assigns a discrete value to a pixel by thresholding a 3×3 neighborhood window of pixels with the center pixel value and considering the result as a binary number representation. LBP representation of a given face image is generated by dividing the image into rectangular grids and computing histogram to measure the frequency of LBP values within each grid. The concatenation of all these histograms constitutes the image signature. An extension of this basic approach is to have the neighboring pixels well separated on a circle around a central pixel. The circle can have different diameters and varying number of neighbors to account for textures at different scales. The circular LBP (CLBP) descriptor is computed similarly by thresholding the gray level intensity of pixels with the pixel value of the center of the circle [14]. If the gray level intensity of neighboring pixel is higher or equal, the value is set to one otherwise zero. The descriptor generates the binary representation as:

$$C_{N,R}(p,q) = \sum_{i=0}^{N-1} f(n_i - n_c)2^i, \tag{1}$$

$$f(\cdot) = \begin{cases} 1 & if \quad n_i - n_c \geq 0 \\ 0 & otherwise \end{cases}, \tag{2}$$

where n_c corresponds to the gray level intensity of center pixel of the circle and n_i corresponds to the gray level intensities of N evenly spaced pixels on a circle of radius R. High discriminative power of circular LBP features favors its use in local region description. Moreover, circular LBP is a local descriptor, therefore it is fast to compute and robust to pose, illumination and expression changes.

B. Proposed Algorithm for Recognizing Newborns

The steps involved in the proposed newborn recognition algorithm are illustrated in Fig. 3. As mentioned earlier, the information present in the image changes with expression and pose. For example, in the face images shown in Fig. 1, there are wrinkles and blurriness present in some images whereas others contain good quality images without the challenge of any covariate. The effect of such artifacts can be minimized using Gaussian smoothing. Thus, two levels of Gaussian smoothing is applied to ensure that excessive wrinkle information is adequately filtered while preserving discriminating texture information. To extract features from the original face images and two Gaussian smoothed images, SURF and LBP are applied. LBP features are extracted from low frequency images while SURF features are extracted from the original image. Fig. 4 shows the SURF and LBP features extracted from the original and Gaussian smoothed images. The details of the proposed recognition algorithm are described below:

- For a given image, face region is detected and resized to 200×200 pixels. Facial image is convolved to obtain a set of low pass filtered images, the Gaussian Pyramid. If G_0 be the original image (the lowest level of the Gaussian Pyramid), then G_l, the l^{th} layer of the Gaussian pyramid is given by:

$$G_l(i,j) = \sum_{m=-2}^{m=2} \sum_{n=-2}^{n=2} w(m,n) G_{l-1}(2i+m, 2j+n) \tag{3}$$

  such that $(0 < l \leq N', 0 < i \leq C_l, 0 < j \leq R'_l)$. N' is the number of layers in Gaussian pyramid, C_l is the column number of the l^{th} level and R'_l is the row number of the l^{th} level of Gaussian pyramid, $w(m,n)$ represents a Gaussian kernel with dimensions of 5×5 and a reduction factor of four.
- SURF descriptors are detected on the original image. This descriptor provides scale and rotation invariant information from the lowest level (G_0) of Gaussian pyramid.
- Moving down the Gaussian pyramid, the size of image decreases and we do not get sufficient number of interest points in the images at Gaussian level 1 and level 2. Therefore, circular local binary patterns is applied at level 1 and level 2 to capture the discriminating texture information from these levels.
- Chi-square distance measure is used to measure the dissimilarity between the corresponding levels of Gaussian pyramid. Let s_0, s_1 and s_2 be the min-max normalized scores for each level of Gaussian pyramid.
- Finally, weighted sum rule fusion [15] is applied to combine the three match scores,

$$s_{fused} = w_0 \times s_0 + w_1 \times s_1 + w_2 \times s_2 \tag{4}$$

  where w_0, w_1, and w_2 are the weights assigned to different levels of Gaussian pyramid and s_{fused} is the fused score. In the experiments, $w_0 = 0.9, w_1 = 0.05$ and $w_2 = 0.05$ yield the best recognition performance.

IV. Performance Evaluation

A. Newborn Face Database

There are several face databases that are available in the public domain but none of them contains images of infants. To evaluate the performance of the proposed algorithm, a face database is prepared that contains 374 images pertaining to 34 babies. For every baby, 10-14 images are captured in two sessions. The first set of photographs are captured within

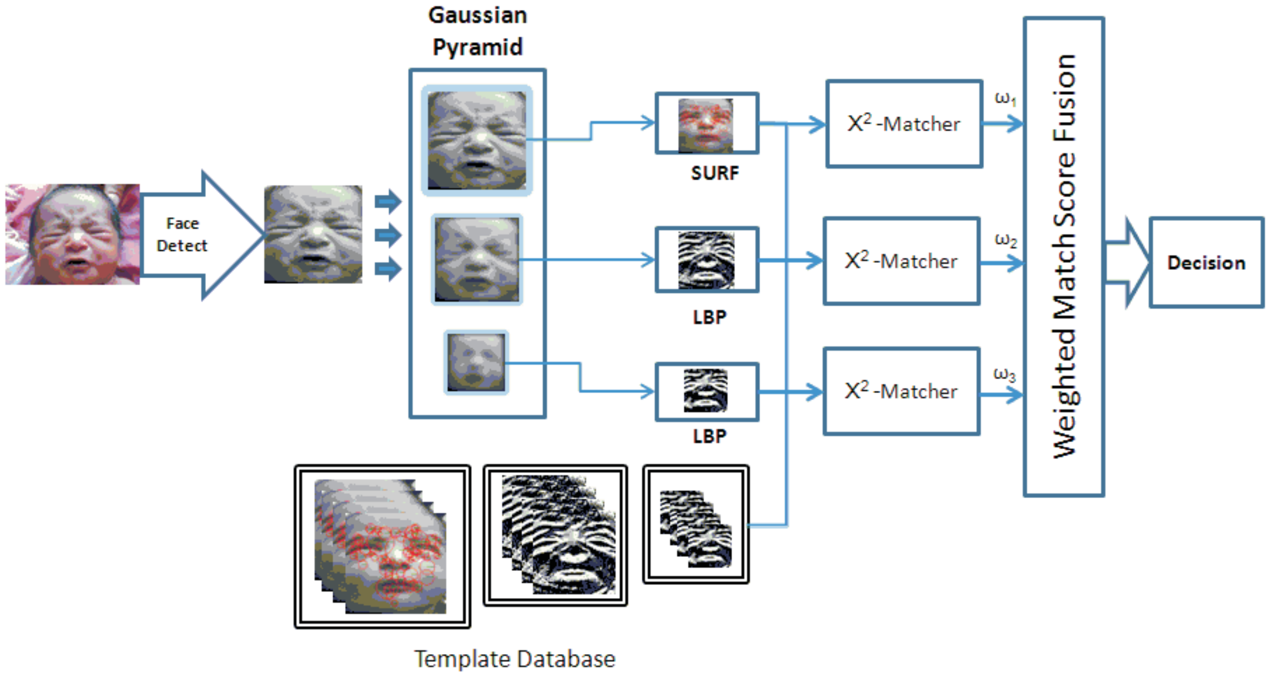

Fig. 3. Illustrating the steps involved in the face recognition algorithm.

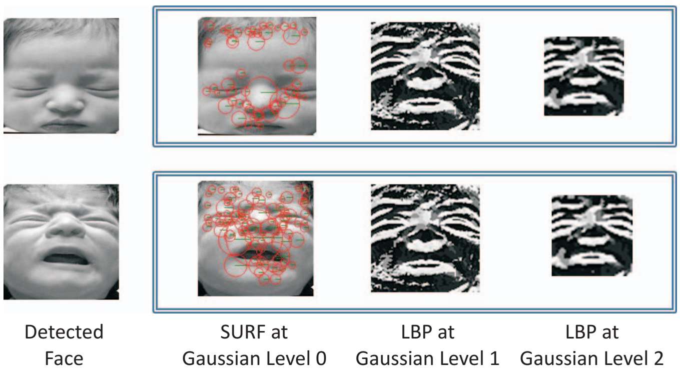

Fig. 4. Illustrating the features extracted at different steps of the face recognition algorithm.

2 hours of birth and another set is at the time of discharge which is 8-15 hours after birth. Out of these 34, there is one pair of twins (shown in Fig. 2(a)). These images are captured without applying any constraint on the newborn or the surroundings, and hence the database contains images with pose, expression and minor illumination variations. Due to the movement of the babies, there are some instances of motion blurriness also. Fig. 5 shows sample images of two babies from the database[2].

B. Experimental Protocol

To detect the face images, initially Adaboost based face detection [16] was implemented. However, one of the important features of Adaboost is eyes and in a large part of the database, eyes of the babies are closed. Further, there are several images with non-frontal pose. Adaboost yielded high number of incorrect face detections in these kinds of images. To remove the detection errors, faces were manually detected. Geometric normalization (or affine transformation) was used for face alignment and the intereye distance was set to be 100 pixels.

For performance evaluation, the database was partitioned into two parts: training/gallery and probe. Four images of each baby were randomly selected for training/gallery database (total of 136 images) and the remaining 238 images were used as probe. The training/gallery and probe partitioning was performed five times for cross validation and rank

[2]We are expanding the database and have made it available to the researchers, via email request, for non-commercial purpose.

Fig. 5. Sample images of two babies from the database.

1 identification accuracies were computed.

The performance of the proposed algorithm is compared with SURF and LBP along with three appearance based algorithms using our modified version of the publically available source code [17]. The three appearance based algorithms used for comparison are:

- Principal Component Analysis (PCA) [18]
- Linear Discriminant Analysis (LDA) [18]
- Independent Component Analysis (ICA) [19]

C. Experimental Analysis

The performance of the proposed algorithm is evaluated and compared with existing algorithms. The identification accuracy of all the six face recognition algorithms (PCA, LDA, ICA, SURF, LBP, and the proposed) are computed on the newborn face database. The results of this experiment are compiled in Table I and Fig. 6 and 7. The key analysis are explained below:

- Table I shows that among the appearance based algorithms, ICA yields the best accuracy of 84.61% at the zeroth level of the Gaussian pyramid. The performance of appearance based PCA and LDA algorithms increase with increasing the levels of the Gaussian pyramid i.e., decreasing the resolution of the image.
- For local texture based algorithms, SURF gives the maximum accuracy at level 0 whereas for LBP, it was observed that the performance of LBP increases with increasing the levels of Gaussian pyramid. This shows that LBP yields better performance with images smoothed by applying Gaussian pyramid.
- Since the performance trend for higher level of Gaussian pyramids is similar for LBP and appearance based algorithms, correlation analysis was performed to determine the feature extractor that can provide maximum complementary information. The correlation value of SURF at level 0 and LBP at level 1 was very low and therefore, it justifies the application of SURF features at level 0 and LBP features at levels 1 and 2 in the proposed algorithm.
- The performance of the proposed algorithm is computed with five times random cross validation. The average rank 1 identification accuracy is observed to be 86.97% with a standard deviation of 2.175.
- The performance of the proposed algorithm negates the human (adult) perception that children's faces look alike.

V. Conclusion and Future Work

Baby switching and abduction are very important problems across the world. Several biometric and non-biometric techniques have been evaluated to reduce the number of such incidences. Biometric techniques include footprint, fingerprint and palmprint with human experts performing the matching. This research performs a preliminary study on using automatic face recognition for identifying newborns. SURF and LBP based face recognition algorithm has been proposed that extracts local texture features from different

TABLE I
IDENTIFICATION ACCURACY OF THE PROPOSED AND EXISTING ALGORITHMS ON THE NEWBORN FACE DATABASE.

Algorithm	Gaussian Level	Identification Accuracy (Rank 1)
PCA [18]	0	73.4 %
	1	79.8 %
	2	81.3 %
LDA [18]	0	79.8 %
	1	79.8 %
	2	80.7 %
ICA [19]	0	84.6 %
	1	75.0 %
	2	75.4 %
SURF [12]	0	82.4 %
	1	62.1 %
	2	0.0 %
LBP [13]	0	76.0 %
	1	79.2 %
	2	80.1 %
Proposed	-	86.9 %

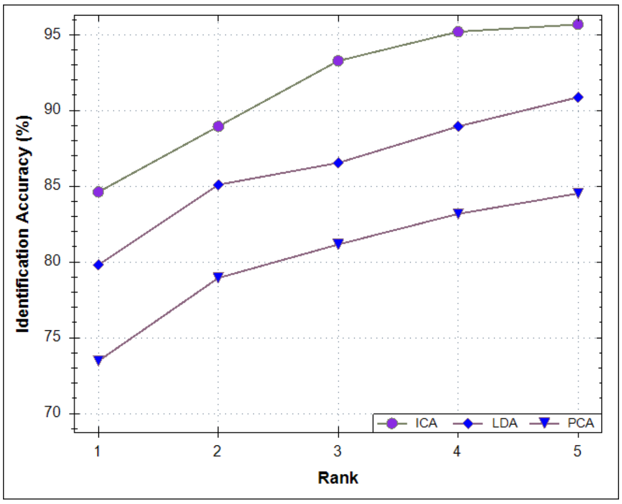

Fig. 6. CMC for appearance based face recognition algorithms at Gaussian level 0.

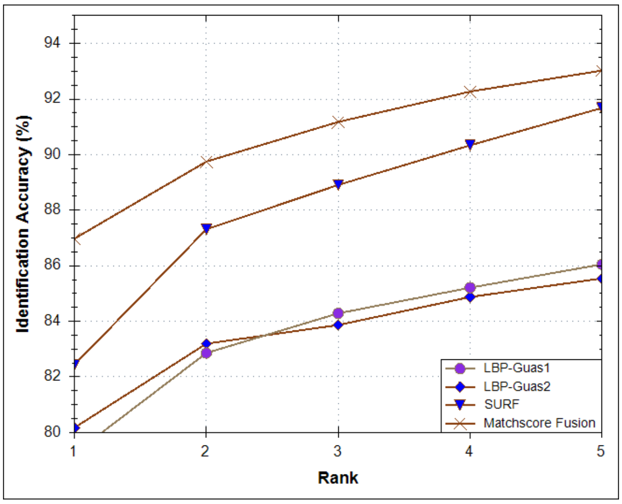

Fig. 7. CMC to show identification accuracies of individual components of the proposed face recognition algorithm.

levels of Gaussian smoothed images. Experimental results on a database of 34 newborns show that automatic face recognition for newborns is feasible. In future, we plan to extend the database in size to perform a more large scale evaluation of the technique. Another relevant study is to collect images of newborns after a couple of months and then analyze the efficacy of face recognition in newborns.

VI. Acknowledgment

Authors would like to thank Brian C. Becker for providing some of the source codes used for evaluation. Authors would like to thank the Institute of Medical Sciences, Banaras Hindu University, Varanasi, India and Mr. Shirkant Tiwari for their support in collecting the databases used in this research.

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