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Evolution in Children Fingerprint Recognition Approaches: A Review

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Abstract: Biometric as an identification tool for children recognition is started in the late 19th century by Sir Galton. However, it is still in the developing stage even after the span of two centuries. The main hurdles in this process are the small size, non-uniform growth of different biometrics and lack of public databases of children biometrics. The authors have touched all the aspects of fingerprint recognition of children. Childhood is very important and crucial in the life of human beings. Most important vaccinations are given in these years. Children are not able to take care of themselves therefore swapping, abduction and missing happens in this age. The main objective is to reveal the progression study of children's recognition for the age group of 0 to 5 years. The combination of transform domain features and machine learning classifiers gives good accuracy of identification of children. Also, multimodal fusion and deep learning approach will increase the identification accuracy of the children.In this paper, a complete survey of studies done for children recognition using physiological biometric is covered. Detailed discussion on database availability, scanning devices, feature extraction techniques, growth models used and matching algorithms is presented. Fingerprint modality is explored using their trends and challenges. Also, the effectiveness of fingerprint modality for recognition of children is discussed.
Keywords: Biometrics, children, convolutional neural network, fingerprint, recognition

1. INTRODUCTION

The children population of age group 0 to 4 years is 110,447,164 in India [1]. Every child is very special and adorable to their parents. Most care is taken by their parents in their childhood. However, there is a chance of abduction when they are in hospitals. Since most of the hospitals use manual methods of identification of infants. The rate of abduction and missing children is very high. From the report of the International Centre of missing and exploited children, more than 1 million children are missing every year [2]. There is an increasing need to identify children individually. Children are in the developing stage till their adulthood. They go through biometric growth along with the physical growth. Therefore, identifying them by their biometric is challenging. Even then researchers have done remarkable study in this area. The biometric modalities used for the recognition of adults can be used for the children as well. The footprint[3], [4], [5], [6], [7], [8], [9], [10], [11], [12] and fingerprint modalities are studied more for children recognition among all other modalities. The palmprint, face [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], ear [24], [25], [26], [27], iris[28], [29], [30], [31] and headprint [32] are least studied modalities. These Physiological biometric modalities are mentioned in the Figure 1

Figure 1. Biometric modalities used for children recognition in literature: Headprint, Face, Iris, Ear, Fingerprint, Footprint, Palmprint

The basic biometric recognition process for the children is same as the adult biometric recognition, it is shown in Figure 2. The first step is image acquisition. The scanning device plays an important role in capturing the minute details of children's biometrics. However, most of the commercially available devices of fingerprint scanning are made for adult biometrics. The number of images captured needs to be large enough to study the latest algorithms. The database creation is critical and time consuming as childrens are in a playful mood. They are unconstrained subjects. The pre-processing of databases is a major task in children recognition as the data acquired is in miniature form. We need to convert the database according to the requirement of

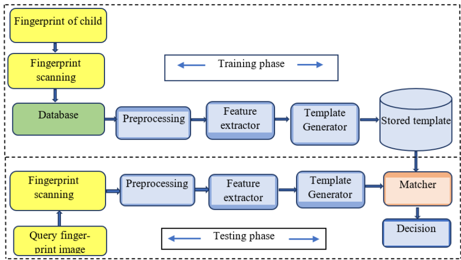

Figure 2. Blockdiagram of biometric recognition of children

software defined kits (SDK) or models by pre-processing. The most critical step is the feature extraction. Again, the features are in tiny size, hence growth models need to be incorporated for increasing the size of features or to match the features after time lap. Extracted features are stored as templates in the training phase. Later during the testing phase, features derived from fingerprints are get matched with the stored template

The children's biometric recognition process involves two modes: verification (1:1) and identification (1: N). To solve the critical problems like missing and abduction, identification mode is required while in case of swapping of children verification mode is useful. The accuracy of the algorithms is calculated as, number of correct predictions divided by total number of predictions made.

A. *Objectives and Contributions of the Review*

Biometric recognition of adults has evolved a lot in the last two decades and plays a vital role in their security and healthcare. Child health and security is crucial in early childhood and it can be solved to a great extent using children's biometric study. This review throws light on children's recognition using fingerprint biometric modality. Selection of sensor or scanner, age of child, biometrics selected, database availability, techniques used for recognition; all these parameters are important in child's biometric recognition. The contributions of paper are;

- Almost all children's fingerprint recognition papers are included in the review.
- Detailed review of fingerprint databases is done for the study of fingerprint recognition of children.
- The author has collected the fingerprint database.
- The impact of scanner resolution on fingerprint recognition is also discussed.
- All the methods used for children fingerprint recognition are discussed.

This paper gives holistic survey of children biometric recognition using fingerprint along with open research problems, it's trends and prospects. The paper is arranged as, section 1 gives introduction. In section 2 fingerprint formation in children and scanner evolution to capture details of the fingerprint minutia, availability of the database for research. Section 3 elaborates a special pre-processing means growth model. Section 4 explains different feature extraction and classification algorithms used in literature for fingerprint recognition of children along with accuracy of the different algorithms.Section 5 gives insight on challenges and open issue for the recognition of children followed by conclusion and future scope.

Figure 3. Child and adult fingerprint image [37]

2. Fingerprint formation in Children and Scanning Devices

The formation of finger ridge of human starts in the mother's womb by a buckling acting on the basal layer of the epidermis, which results in the principal ridge. The deformation process is a cause of fingerprint development and is controlled by the stresses formed in the basal layer, not by the curvatures of skin surface. Undulations in the basal layer appear on the fingerprint around 10th week of gestation, becomes more distinct and forms the principal ridges [33]. The ridges on human embryos are observed on fingers, palms and soles. The ridges first appear on the finger, then palm and lastly on the sole of fetus. The ridge pattern formation process completes between the 12th and 16th week in the mother's womb. At the end of the 18th week, the ridges are completely formed and observed on the surface of epidermis [34]. There is a difference of size, prominence, and inchoate between child and adult fingerprints. The inter ridge distance in child fingerprint images is approximately 4 to 5 pixels. To compare with, the adult inter ridge distance is 8 to 9 pixels [35]. The average ridge spacing in children is near about 0.125 mm and the ridge spacing in adults is 0.46 mm [36][60]. The Figure 3. describes the difference between the size and appearance of the child and adult fingerprint. The child ridge spacing is one third of the ridge spacing in an adult.

As per Sir Galton theory, the fingerprint similarity chance in two different people is 1 in 64 billion [38]. This

Figure 4. Commercial off the shelf flat 500 dpi fingerprint scanner [35]

affirmation of Sir Galton showed the potential of fingerprint modality as a feasible solution for identification of children. The small size and vague fingerprints of small children are the main problem in recognizing them. Besides the small size, children's fingers are soft, delicate, dry and wet. In newborn it is observed that their fist is closed. It is due to neurologic reflex which is known as palmar grasp [39]. In the JRC report [40] they concluded that dry finger introduces discontinuity in ridges and results in false prediction of minutia. Wet finger introduces thickness in the line, which makes it difficult to differentiate between ridge lines. Pressure given on the finger also enrolls the fingerprint with reduced ridge spacing.

A. *Fingerprint Scanner evolution for children*

The identification or verification process starts with image acquisition or scanning. This is the first important step. Information loss in this stage could barely be recovered in the next steps. In 1899 Sir Galton delivered the first practical system of fingerprint classification. He has collected fingerprints of a child from 9 days to 4.1 year with the help manual method of fingerprint using ink and paper. The technique used to identify fingerprints is by the human expert. He also studied the young children's longitudinal fingerprint recognition feasibility. Sir Galton said that, 'It would be difficult to rely on the identification of infants after the time lapse'. He inferred that the child can be identified ever after the age of 2 years onwards using his finger prints [38]. After a long span of time the European Commission studied the Fingerprint recognition for children below 12 years (Particularly 6 to 12 years) of age for the Visitors International Stay Admission (VISA) process on request from the European Parliament. They used a fingerprint scanner of 500 dpi as shown in Figure 4. Further studies [40], [41], [42] used the same scanner for fingerprint acquisition. F. Rahmun et.al used a 500-dpi resolution, 4-finger acquisition device. Author enrolled 10 fingers with the help of this scanner. The study conducted to enrol the fingerprints of children, store them as a database and verify the biometric database of VISA applicants in the European countries. They observed difficulties in enrolling the children below 12 years of age [41]. Jain et.al. used the U.are.U 4500 optical fingerprint reader shown in They

Figure 5. U.are.U 4500, 500 dpi fingerprint scanner

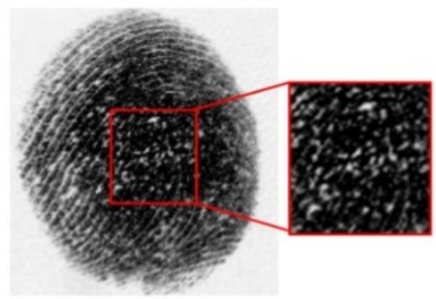

Figure 6. Captured child fingerprint ROI [43]

collected the database of 90 infants and toddlers from Michigan and Benin - West Africa named as Michigan State University's Infants and Toddlers Fingerprint (MSU-ITF) database of 0 to 4 years. The paper demonstrates the importance of proper database collection, they showed that the same software is giving different accuracy on the database collected from two different places with the same scanner. Further the Jain et.al [35] continued their study of the perseverance in fingerprint recognition of children for the age span of 0 to 4 years. They collected 206 infants and toddler's database from Saran Ashram Hospital, Agra, India. They also introduced the NEC PU900-10,1000 ppi scanner in this study. The 1000 ppi resolution scanner was used in manual capture mode. They observed difficulty in manually capturing the fingerprints. Due to manually capturing motion blur was introduced. The study conducted gave the assertion that the fingerprint modality can be used for recognition of children in the age group of 0 to 4 years. Basak et.al used 500 dpi, Cross Match L-Scan slap fingerprint scanner for database collection. These scanners capture more fingerprints at a time. These are used for voter registration, national ID issuance and criminal background check ups [44]. Patil et. al [45] used SupReal Scan G10 Multi Finger print Scanner (Suprema) to capture right and left thumb's fingerprints as shown in Figure 7. Jain et al. used a custom NEC fingerprint reader of 1,270 ppi and

Figure 7

Figure 8. (Acquired child fingerprint with 500 dpi scanner [45]

captured a 6 hours young child fingerprint successfully [46], [47]. Camacho et.al used both the scanners 500 dpi and 1270 dpi. They confirmed that a 500-dpi scanner is good for acquiring fingerprints of children above 1 year old. The 1270 dpi scanner is good for children from 6 month of age [48]. Macharia et. al checked the feasibility of recognition of children based on android based Open Data Kit (ODK). They used 500 dpi scanners for recognition of infants of the age 1 to 12 months. They found fingerprint NFI (National Institute of Standards and Technology (NIST) Fingerprint Identification) quality of level 5 (poor) for 80.5 % children [49]. In 2019, Engelsma et.al [49] designed and developed a high resolution, low cost, compact 1900 ppi fingerprint scanner for children is shown in Figure 11. In 2016, Y. Koda from Nippon Electric Company (NEC) from Japan and the biometric research group from Michigan State University developed a high-resolution complementary metal-oxide semiconductor (CMOS) scanner of Zakuro series (ZAK) - 108 of 1270 ppi and supporting software. Which was effective for capturing child prints is shown in Figure 8 [46] This scanner accomplished enrolling infants from 2 months old. It can recognize infants afterward for an entire year. Further the research continued with this compact, high-resolution scanner by Joshua [51] and got promising results.

Moolla et al.[52] designed a high resolution, contactless scanner for fingerprint scanning for infants is shown in Figure 13. The resolution of the scanner is 2500 dpi with different sized attachments according to age of infants.

Figure 9. (Acquired child fingerprint with 500 dpi scanner [45]

Figure 10. Fingerprint scanner of 1270 ppi

Figure 11. Acquired child fingerprint with 1270 ppi scanner [50]

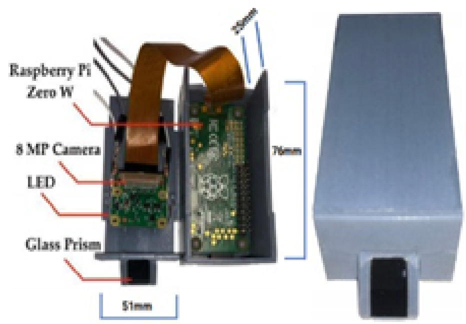

Figure 12. High resolution 1900 ppi, custom, low-cost fingerprint scanner

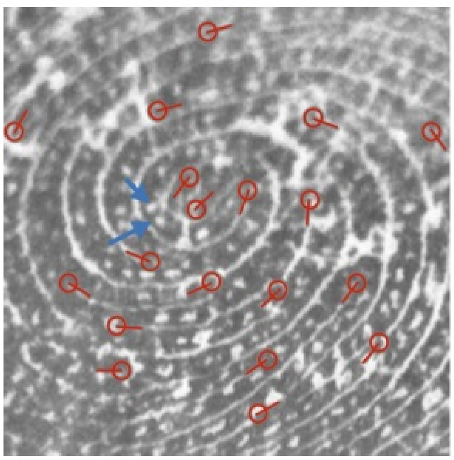

Figure 13. Captured child fingerprint [53]

Moolla et al. [52] designed a high resolution, contactless scanner for fingerprint scanning for infants is shown in Figure 13. The resolution of the scanner is 2500 dpi with different sized attachments according to age of infants.

The second important parameter in the study of recognition of children is database creation. The availability

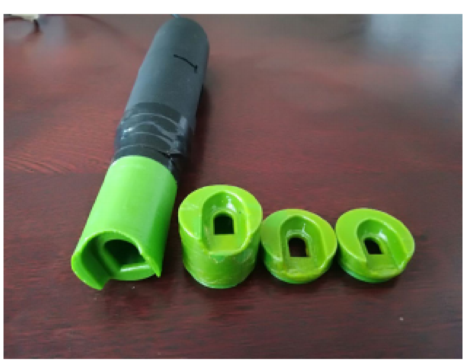

Figure 14. Contactless fingerprint scanner 2500 dpi

Figure 15. Captured fingerprint of infant [82]

of children fingerprint databases for the study is shown in Table 1, which gives the information such as age for enrolment of database, number of subjects, if the database is taken by repeating the acquisition process over the period (longitudinal) or not. Finally, the most important thing, whether the data is available or not for research/study is mentioned. All the databases are private due to the protection of the identity of children. The longitudinal Children Multimodal Biometric Database (CMBD) and National Institute of Technology Goa's (NITG) are the only databases available for research purposes. It is a great help for the young researchers in the fingerprint domain. The author is also collecting the database of children fingerprint of zero to six years. Up till the same session database of 87 subjects is collected. Total images in the database are 4350 as ten fingerprints of each child is taken five times.

The major hurdle in recognizing children longitudinally is biometric aging. Describing the growth pattern of a child fingerprint has the key role in the identification process. A study conducted between 2009 and 2010 by Gottschlich et. al [54] focussed-on growth of fingerprints in children. They did systematic analysis and modelling of the growth pattern of fingerprints. For the study, they took a longitudinal database of juveniles, above 12 years from the Federal Criminal Police Office of Germany. They worked on the assumption that ridge distances follow the similar growth chart as the body length. In this report, they presented the fingerprint growth chart, which shows that the growth follows an isotropic rescaling. This can co-relate between growth in height of children to the growth of fingerprints.

The rescaling of minutia according to Gottschlich growth chart shows 72 % reduction in the distances between similar minutiae after the time lapse. They noted that low contrast and distortion in image was the final hurdle for children's fingerprint recognition. The European Commission published the report* with the objective that children fingerprint size changes in the age range 6 to 12 years according to the growth pattern of children [35].

3. Fingerprint Growth models

The major hurdle in recognizing children longitudinally is biometric aging. Describing the growth pattern of a child fingerprint has the key role in the identification process. A study conducted between 2009 and 2010 by Gottschlich et. al [54] focussed-on growth of fingerprints in children. They did systematic analysis and modelling of the growth pattern of fingerprints. For the study, they took a longitudinal database of juveniles, above 12 years from Federal Criminal Police Office of Germany. They worked on the assumption that ridge distances follow the similar growth chart as the body length. In this report, they presented the fingerprint growth chart, which shows that the growth follows an isotropic rescaling. This can co-relate between growth in height of children to the growth of fingerprints.

$$gf^{T_0}(T1) = \frac{(gf^5(T0))}{(gf^5(T_1))} \quad \text{for} \quad T_0 \in [6,16] \quad \text{and} \quad T_1 \in [6,16] \tag{1}$$

Where gf= Growth factor,
T_0 = Enrolment age and T_1 = Age after time lapse.

They introduced the minutiae-based growth model for the age from 5 to 16 years using NIST BOZORTH3 software. The model gives the growing fingerprints (of T0) to match with time T1. Also, gives the rejuvenate fingerprints by contracting (of T1) to match with T0. They concluded that the displacement of minutia is isotropic, in the age 6 to 16 years. The displacement growth coefficients are linear with themselves and with height of the children in that age. Moreover, the growth coefficients of displacement increase half the rate of height increases at that age. They have given a growth model as shown in equation 1, where the age range is from 6 years to 16 years. By using the growth model, a large improvement in the Genuine match score was observed. In some cases, the improvement was 80 % with a large time difference between T0 and T1. It is to be noted that the growth model is done for higher age, the age range considered by the author is 5 to 16 years. Study of growth model on infants and toddlers remains an open research problem.

4. Feature extraction and classification algorithms

Most of the children's fingerprint recognition study used the readily available Automatic fingerprint Identification Systems (AFIS) and Commercial off the shelf matcher (COTS) for feature extraction and matching. European (JRC)*[1] study reports used BOZORTH3, Vendor1 and 2 are the three State-of-the-art commercial solutions for feature extraction and matching [35].

Jain et.al [43] explored the practicability of fingerprints for identification of infants and toddlers for the application of children immunization through vaccination. They used a commercial fingerprint Software Development Kit (SDK). However, all commercial matchers are designed for adult biometrics. As mentioned earlier, children's fingerprints are one third of the adult fingers. Children's fingerprints need to be made large to the size of adult fingerprints by resizing them. The scanned fingerprint upsampled to facilitate minutiae extraction with a fixed scale factor of 1.8 based on observations. A rank-1 accuracy 98.97 % and 67.14 % is observed using state- of -the-art matchers used for latent fingerprints on the MSU-ITF database collected from Michigan and Benin - West Africa. The difference between accuracy in COTS SDK and latent fingerprint matcher is because of the quality latent fingerprint exhibits, which resembled the children's fingerprints. The performance improvement was observed by fusing the match score of thumb and index finger. For children identification latent fingerprint matchers were more suitable than Commercial SDK as children's fingerprints were more like latent fingerprints. Jain et.al [55], [56], [57] continued their study of children recognition using COTS, tenprint and latent fingerprint SDKs. In this study also, they upsampled the fingerprint image of the child by a constant factor of 1.8. It is done by the imresize function of MATLAB's before feeding them to the SDKs. The upscaling of the children's fingerprint is necessary to make sure that the ridge spacing of children (4-5 pixels) is nearly that of adults (8-9 pixels), which can facilitate feature extraction using the SDKs. They concluded as 1) Using more than one finger for verification was notably better than using a single finger. 2) After 12 months, the children's recognition performance was stable. In the next research, Jain et.al [46] used state-of-the-art AFIS. Two scanners were used, 500 ppi with 1.8 up-sampling and 1270 ppi with 0.71 down-sampling factor for the fingerprint of children. They said that the age of child at the time of enrolment had more impact on the result of AFIS than the time span. Jain et. al. [47] took a new approach for fingerprint enhancement instead of upsampling. They designed the Convolution Neural Network (CNN) for enhancing the images. By using CNN enhanced images, they performed verification (1:1 comparison) as well as identification (1: N comparisons) using a commercial fingerprint SDK. As CNN requires more images for training, The VaxTrac4 database was added to the existing database. So extra 16,384 infants and 32,768 fingerprints get added to the experiment database. Rank1 identification accuracy of 38.44 % was achieved for infants less than 4 week and 73.98 % for greater than 4 weeks. Chamacho et.al [48] used pre-processing of the fingerprint to feed to the AFI system. They performed pre-processing in two steps, interpolation (as done by A. K Jain [43]) and segmentation. Also, they concluded that the bi-cubic was the simple and better choice for interpolation by comparing the methods; Geometric Contour Stencils, Tensor-Driven Diffusion. In this study, they use an interpolation factor based on age of child instead of fixed interpolation factor

1.8. The interpolation factor is calculated with the help of equation 2.

$$Factorofinterpolation(foi) = \frac{(Distancebetweenridgesonadults)}{(Distancebetweenridgesonagegroup)} \quad (2)$$

If the inter ridge distance of child below 1 month was 5.92 then interpolation factor will be as in equation 4

$$Factorofinterpolation(foi) = \frac{9}{5.92} \quad (3)$$

If the inter ridge distance of child below 1 month was 5.92 then interpolation factor will be as in equation 4.

$$\therefore Factorofinterpolation(foi) = 1.52 \quad (4)$$

TAR (True acceptance rate) of 98.3 % is achieved for the age group of 5 years. TAR of 79.28 % is achieved for the age group of 1 year. Haraksim et. al [56] extended the study of Gottschlich et.al. They verified the ageing effect on children's fingerprints with the help of a fingerprint growth model. By using generalized minutia growth models with NIST BOZORTH3 software, they observe significant growth in verification accuracy. Enselgma et. al [53], gave a solution as "Infant-Prints" which was obtained from the high-resolution scanner developed by the author, high resolution fingerprint matcher based on CNN and a mobile application for verification of children.

A custom, compact, low-cost, 1900 ppi resolution scanner was developed. Due to the use of texture-based CNN matchers, they do not need to down sample the fingerprint images of children. They used different fingerprint matchers, COTS-A, COTS – B (a latent fingerprint matcher) and texture-based CNN. Highest accuracy was observed by fusing the results of all three matches. For the first time, they showed the TAR of 75 % at 0.1 FAR (False Acceptance Rate) at the age of 1 month and TAR of 90 % at 0.1 FAR for the age 2 months. Patil et.al [45] did not use any COTS matches. They developed their matching algorithm using Euclidean distance to verify the children. The enhancement method is based as mentioned [58]. They first enhanced the image of children by applying Short Time Fourier transform (STFT). The features are extracted using two 1D Gabor filters. The verification accuracy of children was 73.95 % on CMBD database and 83.12 % on NITG database using right thumb of child. Preciozzi et. al. [55] extended the work of Chamacho [48]. They used commercial implementation of AFIS for verification purposes. As mentioned in paper [48], pre-processing consisted of an interpolation and segmentation. With the help of pre-processing, the quality of children's fingerprints improves to the adult standard. To increase the accuracy, two fingerprint results are fused at score level fusion. The scaling factor used is 1.8 as done by Jain et. al [47]. Recognition accuracy of 98.33 % is achieved for five-year-old children and one year old children accuracy was 81.42%. Engelsma et. al. [51] used a high-resolution scanner 1900 ppi. They used deep networks in all stages of fingerprint recognition. The enhancement was done by improving the sharpness and clarity of the children's friction ridge pattern using the Super Resolution Model 'Residual Dense Network (RDN)'. Minutiae aging was done by using a scaling factor of = 1.1, which was decided by means of observation (empirically). Minutiae Extraction was done with a fully-convolutional auto-encoder. For training of the autoencoder network, manually minutiae markup images were used. They used 3 matchers for analysing the matching accuracy. Minutiae match score with Verifinger 10 which is ISO minutiae matcher, texture CNN matcher and latent fingerprint matcher. Final match score (Sf) is calculated by fusing the matching score of all matchers by multiplying with constants as given in equation 5. sf= m.sm+ t.st+ l.sl (5) Sf = (0.6 *Combined minutiae match score (sm) + 0.1 *texture match score (st) + 0.3 * latent match score (sl)) This showed accurate recognition of infants registered at 2 to 3 months and authenticated 3 months later with the accuracy of TAR=95.2% for the specified FAR=1.0Kamble et al [58], [59], [60], [61] combined the transform domain, Curve Discrete Cosine Transform features and machine learning classifier to achieve the accuracy of 96 % for identification of children. The transform domain deep learning approach is also applied to check the accuracy of children identification. This method shows the accuracy of 92 % for identification of children. Summary of all the methods used for fingerprint recognition with the resolution of the scanner used along with accuracy is given in table 2.

Children recognition in the same session using biometrics has achieved high accuracy even with the hurdles of capturing biometric images. Most of the biometrics show high accuracy using recent machine learning and deep learning algorithms. However, longitudinal children recognition using different physiological biometric modalities is still challenging. Research done in this area is minimal. The database availability for the research purpose is very little. Researchers have collected the databases but they have not shared it due to security issues of children. In the image acquisition devices fingerprint devices are well developed in terms of resolution and shape. Commercial fingerprint scanners are available for children recognition. However, commercial SDK is not available for children recognition.

Fingerprint modality is well studied and good for recognition of children. The minimum age of accessing the fingerprint is 6 hours [47]. According to Jain et. al. the same session fingerprint accuracy is least affected by different algorithms instead age of child is the crucial factor in accuracy. In cross session minimum age of enrolment is the main factor, which affects the accuracy of the algorithm. To capture touchless fingerprints, we need a high-resolution camera. However, the fingerprint images captured with the camera are not clear, that is the ridge and valley pattern is not much distinct. Hence fingerprint scanner needs to be used.

TABLE I. Databases created to study fingerprint recognition of children since 1899

Database	Age	Number of subjects	Longitudinal study	Availability of database
Sir F. Galton [38]	9 days to 4.1 year	1	Yes	Not available
Portuguese Passport database [35]	0-12 years	1632 subjects 3264 pairs of fingerprints (Two index fingers)	Yes	Private
	5 -17 years [11]	60,000 children's fingerprints	Yes	
[1]MSU-ITF [35], [43]	0-4 years	2020 fingerprints of 90 subject's left index and thumb	No	Private
Saran Ashram, India [43], [50], [53], [51]	0 -4 years	1,164 images of 206 children	No	private
	0 -5 years	309 children	Yes	
	0-3 months	194 newborns	Yes	
	0-12 months	315 infants	Yes	
[2]VaxTrac,	–	32768 fingerprints of the left and right thumb of both mother and child.	No	Private
[3]DNIC3 [48], [55]	children from age 0 to 10	5 to 6 years 1400 subjects and in the age range of 0 to 1 month1300 subjects were present	Yes	private
	0 to 12 years	Total subjects selected for database were 16865 with total fingerprints of 178843	Yes	
** CMBD [44], [45]	18 months - 4 years	119 subjects 11350 fingerprint images of all 10 fingers 5 samples	Yes	Public
*** NITG [45]	0-4 years	154 children,5 fingerprints of each thumb	Yes	Public

*MSU-ITF Michigan form US, Benin from West Africa database, **VaxTrac is a clinic-based vaccination registry system, ***Uruguayan National Identification Agency's database, ****IIIT Delhi's Children Multimodal Database, *****National Institute of Goa's database.

5. Challenges and open issues of recognition

Trained person needed to capture the proper fingerprint of children. Fingerprint is a mid to high frequency image, hence texture-based algorithms can give good accuracy. One can achieve high accuracy of the same session database using traditional algorithms.

To achieve high accuracy of the cross-session database deep learning algorithms need to be used. These deep learning models need to be tuned with respect to hyper parameters according to the input modality. Transfer learning models can be used to learn deeper features and to improve the accuracy. The major requirement of the deep learning models is a large dataset. This problem can be overcome by incorporating data augmentation techniques.

Conclusion

Children safety and healthcare is the major priority throughout the world. Still the research done in the recognition of children is minimal. It is due to unavailability of the children's biometric databases for research. This paper gives a brief outlook on fingerprint biometric of children, its scanning devices, databases, pre-processing, feature extraction and matching. Capturing biometric images itself is a challenge in children and contains less information if captured with low resolution devices. Hence scanners/cameras need to be of high resolution to capture these images. Further good amount of research is required at every stage of children's biometric recognition- progression model, pre-processing, feature extraction and matching. After reviewing almost all papers for recognition of children using fingerprint modality, it can be concluded that most of the work done is in verification mode. In contrast, research needs to be done in identification mode. Longitudinal study is important in the recognition of children at the same time it is critical as changes in their modalities are fast and drastic. Longitudinal study of children's biometrics is still an open research problem. The fingerprint modality has not reached adult biometric recognition standards. To get higher results in longitudinal recognition more than one modality can be used. Multimodal fusion is one of the options to solve the problem of biometric recognition of children. Children's biometric recognition is a need of society in today's world. This research review will benefit several researchers, hospitals, Government agencies, National ID schemes and an individual parent.

Futur scope

Fingerprint modality of the children can be used in recognition of children. There are less changes in the fingerprint over the period as compared to other modalities such as face. Large database needs to be collected to train modern deep algorithms. Multimodal fusion will also improve the accuracy of the recognition.

TABLE II. Table 2. List of Fingerprint recognition methods with their accuracy

Author name	Objective of research	Scanner resolution	Pre-processing	Feature extraction and matching	Accuracy
Kamble et al 2023 [61]	Biometric Identification of children	5ppi	ROI extraction using slope technique	DCT,CDCT,CNN	99 % Max Fuctions of algorithm
Kalisky et al 2022 [60]	Biometric recognition of newborn, children for vaccination and healthcare	5MP	NA	NA	$\geq 99\% with multiple fingerprint$
Moolla et al 2021 [59]	Review of Infant biometrics	NA	NA	NA	NA
Engelsma et al 2020[51]	Low-cost, high-resolution fingerprint reader, high-resolution infant fingerprint matcher.	1900 dpi	Super resolution model, Residual Dense Network	Fusion CNN + two COTS matchers	TAR = 95.2 % at FAR = 1.0%
Patil et al 2019[45]	Design an efficient fingerprint recognition system for infants and toddlers	500 ppi,	Short-time Fourier transform (STFT), 1-D Gabor filter	Gabor filtering, Euclidian distance.	NITG = 83.12 %, CMBD = 73.95 %
Engelsma et al 2019[53]	To reduce the death of infants due to vaccine-preventable diseases, malnutrition	1900 ppi	Not discussed	CNN, COTS-A, COTS-B	TAR 90 % at 0.1 % FAR for infants older than 8 weeks
Haraksim et al 2017[56]	To reduce the problems occurred due to biometric aging of fingerprints of children.	500 ppi	Not discussed	Minutiae-based growth model, NIST BOZORTH3	The displacement of minutiae points follows an isotropic mode.
Basak et al 2017 [44]	To solve the problem of enrolment in law enforcement, attendance system, medical services.	500 dpi	Segmentation done using NFSEG (NBIS) tool and manually	MINDTCT and Bozorth3.	97.07 at 0.1 % FAR for intra modality fusion.
Preciozzi et al 2020[55]	Starting age for digitally acquired fingerprints of children and comparison of children fingerprint with adult.	500 dpi	Age dependent scale factor, bicubic interpolation	Not discussed.	TAR 5 year 98.33 and 1 year 79.28 with fusion of two finger and proposed scale factor
Macharia et al 2017 [49]	To improving HIV - follow up of infants and facilitate quality care and treatment to them.	500 dpi	Not discussed	ANFIQ	80.5% (416) had an NFIQ score of 5
Camacho et al 2017 [48]	Robustness of fingerprints to identify children on an on-production civilian database	500 dpi 1270 ppi	Interpolation factor based on age of child.	Interpolation factor used is based on ridges distances.	TAR of five-year old children 90.65 %, one year 81.42 %
Jain et al 2016 [47]	To develop a fingerprint-based identification system for infants (age range: 0-12 months)	1270 ppi	CNN is used to improve Image quality	Commercial fingerprint SDK	Age Group Rank-1 (%) ¡= 4 weeks 38.44 ¿ 4 weeks 73.98
Jain et al 2016 [46]	Investigating the persistence of genuine scores from child fingerprints using mixed-effects statistical models.	500 ppi 1270 ppi	The 500 ppi images are upsampled by of 1.8 and 1,270 ppi are downsampled by of 0.71	AFIS	12 months of age TAR = 99.5% at FAR = 0.1%, 6 months or older TAR = 98.9 % at FAR = 0.1%
Koda et al 2016 [50]	Designed to capture child fingerprint (0.1 mm ridge spacing) high resolution Fingerprint Scanner and software	1270 ppi	Designed Fingerprint Scanner	High resolution CMOS image sensor combined with an image enhancement	NA
Jain et al 2016 [57]	To investigate the persistence of fingerprint recognition for children in the age group of 0-4 years.	500 ppi 1000 ppi	All fingerprint images are upsampled by a factor of 1.8	COTS SDKs, a tenprint SDK (COTS-T) and a latent fingerprint SDK (COTS-L).	Average fusion of the comparison score is used as the final score.
Jain et al 2014 [43]	To solve the problem of Vaccination Coverage of countries in West Africa	500 ppi	Upsample the acquired fingerprint image to facilitate minutiae extraction with a fixed scale factor of 1.8 based on observations.	Commercial fingerprint SDK.	A rank-1 accuracy 98.97 % and 67.14 % is observed using state- of -the-art latent fingerprint matcher on two databases

Conflicts of Interest

Both the author has no conflict of interest

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