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Article

# A Longitudinal Study on Fingerprint Recognition in Infants, Toddlers, and Children

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**Abstract:** Millions of children in developing countries face preventable deaths due to inadequate vaccination and malnutrition, in part due to insufficient monitoring and the absence of official identification. A reliable fingerprint recognition system can be a practical solution to address this issue. However, the scarcity of longitudinal fingerprint datasets for young children leads to unresolved questions regarding the earliest age for fingerprint biometric use, the frequency of enrollment required for reliable recognition, and the methods to accommodate age-related changes. A few recent studies introduced high-resolution fingerprint scanners and showed promising recognition performance for young children. However, these studies were conducted on a small dataset over a shorter period with limited diversity; further evaluation of their finding is essential. This study assessed the effectiveness of a high-resolution contactless scanner in a controlled, diverse longitudinal dataset of children (0-15 years). Our results indicate that infants can be enrolled at five days old and reliably recognized after two months with a TAR= 100% @ FAR = 0.1%, and children aged 4-15 years can be recognized after one year with a TAR= 98.72% @ FAR = 0.1%.

# 1. Introduction

Annually, 20 million children fail to receive the essential annual vaccinations they require, resulting in a tragic toll of 1.5 million children deaths caused by vaccine-preventable diseases[?]. Additionally, 3.1 million children lose their lives globally due to malnutrition [?]. A major factor contributing to this devastating reality is insufficient monitoring and the absence of official identification documents, significantly hampering accurate vaccination tracking and nutritional supplement distribution, especially in developing countries [1]. Biometric recognition for young children can be a viable solution, not only in facilitating the monitoring of vaccination and nutritional supplement distribution but also in ensuring border security, preventing newborn swapping, combating child trafficking, and providing access to healthcare, civil IDs, and so on. However, despite its paramount importance, it remains an ongoing unsolved challenge as the existing biometric technology has proven ineffective for children.

Among various biometric modalities, fingerprint recognition emerges as a promising choice for young children in terms of universality, acceptability, persistence over time from birth, and interoperability across acquisition method [1,4–7]. However, the fingerprint systems designed for adults fail to cater to young children, who possess finer ridge spacing and softer skin compared to adults; using a contact base scanner can cause their fingerprint to flatten against the surface and merge the adjacent ridges, leading to the loss of distinct features. Thus, capturing the fine details of young children's fingerprints necessitates specially designed, child-friendly, non-contact highresolution scanners [5,6]. Figure 1 shows the difference in the quality of fingerprints captured with low- and high-resolution scanners. Additionally, the rapid growth and finger size change in children complicate fingerprint matching over time (aging effect), calling for a system that accommodates these age-related changes. The scarcity of longitudinal fingerprint datasets for children (0-15 yrs.) limits the feasibility of studies on child fingerprint recognition. Consequently, critical questions remain unresolved, such as the earliest age for biometric use, the enrollment frequency needed for reliable recognition, and methods to accommodate age changes. Most of the studies in the literature have been conducted using child datasets captured with low resolution (500 ppi, which is standard for adults) with limited success. A few recent studies using high-resolution fingerprint scanners have indicated

potential for young children, but these studies are limited in dataset size and diversity, necessitating further validation. Additionally, the literature lacks assessments on the effectiveness of high-resolution contactless fingerprint scanners for children over one year old using longitudinal datasets.

Our research addresses these gaps by analyzing data from 254 children (0-15 years) over a year. Our contributions include:

- Assessment of high-resolution contactless fingerprint scanner effectiveness in a controlled, diverse longitudinal dataset of infants, toddlers, and children.
- Determination of the earliest usable age for recognition.
- Study of the impact of age gap between the enrolment and authentication for children.

#### 2. Related Work

In recent years, several studies have focused on the viability of fingerprint recognition for children. Anil K.Jain et al. [4] conducted a year-long study with 309 Indian children aged 0-5 years, using both a standard 500 ppi scanner and a custom contact base 1270 ppi scanner. Their results indicated that reliable enrollment and recognition were possible at 6 months with 1200 ppi and at 12 months with 500 ppi. Galbally et al. [2] analyzed a dataset of approximately 265k different fingers from age groups ranging from 0 to 25 and 65 to 98 years using a 500 dpi scanner and reported that the aging effect profoundly impacts recognition in the 0-4 year age group, with the 5-12 year age group also presenting significant recognition challenges. Precioszzi's [3] research on a dataset of 16,865 identities (0-20 years, images captured with 500 ppi) revealed notably low accuracy for infants (TAR 1.25 to 34.88 @ 0.1 FAR) and children under the age of 5 years (TAR = 61.88 to 78.27 @0.1 FAR) despite introducing a growth factor to counteract the aging effect. Engelsma et al. [1] collected fingerprints from 315 infants aged 0-3 months in India using a 1900 ppi scanner and developed an infant matching algorithm. Their results indicate that infants can be enrolled at 2 months and accurately recognized 3 months later with a TAR 95.2% @ FAR 0.1%. Kalisky et al. [5] introduced a 3400 ppi contactless fingerprint scanner, suggesting that newborns can be enrolled with a single finger as early as 4 days old and recognized within 15 to 30 days with a TAR 96% @ FAR 0.1%. Their research also shows that recognition can achieve a TAR 100% @ FAR 0.1% with a 6-month age gap when enrolled with ten fingers. Table 1 summarizes these prior works.

Table 1. Summary of prior work

Study	Subjects	Enrollment Age	Sensor Reso- lution (ppi)	Time Lapse	Findings			Assessment of sen- sor effectiveness across larger age groups of children	
					Earliest	TAR @0.1	Age	Standard	High
					use-	% FAR	gap be-	Resolu-	Resolu-
					able		tween	tion	tion
					age		enroll-		
							ment		
							and au-		
							thenti-		
							cation		
Galbally et al. [2]	Unknown (256K fingers)	0-25 yrs, 65-98 yrs.	500	0-7 yr	5 yrs	95%	1 yr	Yes	No
Precioszzi	16865	0-20 yrs	500	10 yrs	5 yr	92.64%	10 yrs	Yes	No
et al.				-	-		-		
[3]									
Anil	309	0-5 yrs	500	1 yr	1 yr	99.5%	1 yr	No	No
K.Jain		-	1270	6 m	6 m	98.9%	6 m		
et al.									
[4]									

Table 1. Cont.

Study	Subjects	Enrollment	Sensor	Time	Findings			Assessment of sen-	
		Age	Reso-	Lapse				sor effe	ectiveness
			lution					across la	
			(ppi)					groups of	children
Engelsma	315	0-3 m	1900	1 yr	2 m	95.2 %	3 m	No	No
et al.									
[1]									
Kalisky	494	0-11 m	3400	6 m	4 days	96%	15	No	No
et al.							to 30		
[5]							days		
Ours	254	0-15 yrs	500	1 yr	4 yrs	98.48 %	1 yr	Yes	Yes
			3000		5 days	100%	2 m		

Among the studies mentioned above, Engelsma et al. [1] and Kalisky et al. [5] demonstrated the most promising recognition possibility for infants using high-resolution fingerprint scanners. However, the scope of their trials was limited in terms of dataset diversity, dataset size, and the duration of the study. Additionally, Engelsma et al. [1] reported that the contact base high-resolution scanner performed better than the contactless scanner for infants, whereas Kalisky et al. [5] showed that the contactless high-resolution scanner achieved superior performance than Engelsma et al. [1]. Therefore, further evaluation of their experimental finding is necessary. Furthermore, a literature gap exists in evaluating high-resolution contactless fingerprint scanners for children over one year using a longitudinal dataset. To bridge these research gaps, we collected data from 254 children (0 to 15 years old) over one one-year in the United States using a 3000 ppi contactless scanner (introduced by Synolo Biometrics [? ] ), commercial contact base scanners (500 and 1000 ppi) and performed comparative analysis to assess the effectiveness of high-resolution contactless fingerprint scanner in this age group. Our work can be seen as a contribution to research work conducted by Kalisky et al. [5], aimed at validating their proposed high-resolution scanner and experimental findings.



**Figure 1.** Examples of fingerprints from different ages, captured with 1000 ppi (HID L Scan) and 3000 ppi (Synolo® Neo) scanner.

# 3. Experimentation and Results

In this section, we discuss the preparation of our experimental datasets and the protocol employed for conducting the experiments. Additionally, we provide a detailed explanation of the outcomes derived from our assessment.

# 3.1. Longitudinal Fingerprint Collection

We collected data from local elementary, middle, and high schools for children aged 4-15 years in accordance with an approved IRB protocol. A total of 235 children were enrolled in three sessions starting in October 2022. The time interval between the sessions was approximately 6 months. However, not all the subjects participated in all sessions. The number of participants in each session fluctuated due to new enrollments, absences, and families relocating out of the district. For the dataset of young children, we collected data from the labor/delivery department of the Canton Potsdam Hospital,

NY, USA, and the Canton pediatrician office, in accordance with an approved IRB protocol from our University and St Lawrence Health System. A total of 19 subjects participated since June 2023, including 5 newborns (0-1 month), 10 infants (1 month-1 year), and 4 toddlers (1-3 years). Additionally, subsequent data was collected at their follow-up doctor's appointments. Two images were captured for each finger of each subject. For some subjects, we could not capture fingerprints from all ten fingers due to time constraints. However, in this study, we analyzed only thumb fingerprints. In the manual data cleaning process, images that were improperly captured or showed fingerprint damage from incorrect segmentation were eliminated from the dataset. An overview of the statistics of the dataset is presented in Table 2

Sub Sess.1 Sess.2 Sess.3 Samples Enrollment Time Gap Age 179 235 178 184 4328 4-15yrs. 6m 19 19 204 0-3yrs. various

Table 2. An overview of the dataset

#### 3.2. Sensors

To collect data from children (4-15yrs), a contact-based Crossmatch L Scan Guardian fingerprint scanner with a resolution of 500 ppi and a contactless Synolo® Neo fingerprint scanner [?], with a resolution of 3000 ppi were utilized. For the young children (0-3yr), an HID L Scan with a resolution of 1000 ppi, in addition to the same Synolo fingerprint scanner, was employed. The scanner and captured fingerprint images (both raw and processed) of the Synolo fingerprint scanner are shown in Figure 2. The processed data of the Synolo fingerprint was down-sampled to 500 ppi and adjusted to adult size to ensure compatibility with commercial Matchers.



Figure 2. Synolo® Neo scanner and fingerprint of two months infant.

# 3.3. Image Processing Approach

Synolo fingerprints were processed following the approach described in [6]. For contact fingerprints, we employed slap segmentation (isolating individual fingerprint impressions from a full hand image) using a Mask R-CNN [8] model. We implemented transfer learning approach to fine-tune the Mask R-CNN model (pretrained on the COCO dataset) independently on our Children's dataset and Young Children's dataset. The segmented fingerprint impressions, obtained through the Mask R-CNN model, then served as the input to a commercial matcher (Verifinger [?]).

# 3.4. Fingerprint Matching

To assess how a child's age at enrollment and the time interval between enrollment and the query fingerprint images affect the accuracy of child fingerprint recognition, we performed verification (1:1 comparison) and identification (1:N comparison) experiments using the commercially available Verifinger SDK 13.0 [?]. Additionally, we utilized a specialized mode of Verifinger SDK 13.0, capable of matching fingers of varying scales (child vs. adult), to examine the influence of upscaling a child's fingerprint to adult size on recognition accuracy.

# 3.5. Verification Performance

For verification, True Accept Rate (TAR) @ 0.1 % False Accept Rate (FAR) was calculated. TAR is the rate at which the system correctly identifies and accepts individuals who are indeed enrolled in the

system, whereas FAR is the rate at which the system incorrectly identifies and accepts individuals who are not enrolled in the system. Samples collected at the first session were used as the enrollment, and samples acquired in subsequent data collection sessions were used as the query image. Table 3 and Table 4 show the verification performance of children and young children, respectively.

Table 3. Verification Performance of Children

Enrollment	Sub	Comparison	Resolution	TAR @ 0.1%	TAR @ 0.1%	Time
Age		Count	(ppi)	FAR without	FAR with Scal-	Gap
				Scaling	ing	_
4-15yrs.	156	1869	3000	n/a	98.45%	6 m
4-15yrs.	121	939	3000	n/a	98.72%	1yr
4-15yrs.	163	2000	500	97.79%	97.85%	6 m
4-15yrs.	127	976	500	98.36%	98.48%	1yr

Table 4. Verification Performance of Young Children

Sub ID	Enrollment	Sub	TAR @	TAR @	Time
	Age		0.1% FAR	0.1% FAR	Gap
	8		(1000ppi)	(3000ppi)	1
01-19	0-2yrs.	16	62.26 %	100%	0
10	2 years.	1	50%	100%	1
					month
13	2 months	1	50%	100%	2
					months
11	1 month	1	50%	100%	2
					months
15	1 month	1	n/a	100%	1
					month
05	1 month	1	n/a	100%	18
					days
06	15days	1	0%	n/a	15
	-				days
09	5 days	1	0%	100%	2
					months

Note: Here n/a due to the unavailability of the data for that specific scanner.

Our analysis reveals that subjects enrolled at 5 days old with a 3000 ppi resolution can be recognized after 2 months with a of TAR 100% @ 0.1% FAR, a subject enrolled at the age of 4 to 15 years can be recognized after one year with a TAR 98.72% @ 0.1% FAR. In contrast, fingerprints captured at 1000 ppi show subpar verification accuracy (0 to 50%) for young children (0-3 years). Furthermore, scaling up young children's fingerprints (captured with 1000 ppi) to adult size using VeriFinger SDK 13.0 did not improve accuracy, remaining consistent whether scaled or not. While high resolution was crucial for young children, a 500 ppi resolution sufficed for older children(4-15 years), offering a TAR of 98.4% @ 0.1% FAR after a year, with scaling adjustments making no significant accuracy difference.

Therefore, our analysis underscores that a resolution of 1000 ppi is insufficient to capture the fine details of young children's fingerprints, and a resolution of 500 ppi is sufficient for children over 4 years old. The contactless scanner with a 3000 ppi resolution is found to be suitable for newborns and also provides comparable performance to a 500 ppi resolution for older children.

#### 3.6. Identification Performance

For identification, samples of all subjects captured at the first session were used as the gallery, and samples acquired in subsequent data collection sessions were used as the query images. From the comparison result, a list of the top matches was obtained. The performance evaluation criterion was determined by the Rank-1 hit rate, which signifies the proportion of search queries for which the corresponding matched fingerprint is the top candidate in the list. Table 6 displays the identification

results for children, while Table 5 presents the identification performance for young children's Synolo fingerprints. The analysis of identification performance for fingerprints of young children captured with 1000 ppi was omitted due to very low verification accuracy.

Sub ID Enrollment Sub Gallery Rank-1 Time Gap Hit Rate Age Size with 3000ppi 10 100% 2 years. 16 sub-1 month 13 1 100% 2 months 2 months jects 11 (292 100% 2 months 1 month 15 100% 1 month 1 month sam-05 1 1 month ples) 100% 18 days 09 100%

Table 5. Identification Performance of Young Children

Table 6. Identification Performance of Children

2 months

5 days

Enrollment	Sub	Gallery	Reso.	Rank-1	Rank-1	Time
Age		size	(ppi)	Hit	Hit	Gap
				Rate	Rate	
				with-	with	
				out	Scal-	
				Scal-	ing	
				ing		
4-15yrs.	109	161 subject	s 3000	n/a	97.09%	6
		(341 sample	s)			m
4-15yrs.	121		3000	n/a	96.40%	1yr
4-15yrs.	131	183 subjects	500	95.61%	96.01%	6
		(366 sample	s)			m
4-15yrs.	127		500	97.55%	97.96%	1yr

Our analysis demonstrates a rank-1 hit rate accuracy of 96.40% for children aged 4-15 years using Synolo fingerprints, with a year time gap between enrollment and authentication. Similarly, young children (0-3yrs) exhibit a remarkable 100% hit rate accuracy with a two-month time gap. Conversely, fingerprint capture with a 500 ppi resolution achieved a rank-1 hit rate accuracy of 97.55% for children aged 4-15 years without using any scaling and 97.96% with scaling.

In summary, enrollment in the system at the age of 5 days with a resolution of 3000 ppi allows for successful searches after two months. Additionally, both 500 ppi and 3000 ppi resolutions are effective in accurately identifying children (4-15Yr) after one year.

#### 4. Discussion And Conclusion

Fingerprint recognition for young children can aid in vital areas like vaccination tracking, border security, and combating child trafficking. However, current fingerprint technology falls short for children, primarily due to the variation in finger sizes and the lack of technology tailored to handle these differences. High-resolution scanners show promise for infants, yet their effectiveness across a broader age range in children remains unexplored. Our study investigates high-resolution contactless fingerprint scanners for children aged 0-15 years, focusing on the effects of fingerprint aging. We collected longitudinal data from 254 children using 500 ppi, 1000 ppi, and 3000 ppi scanners over one year. The results show that infants enrolled at 5 days old were accurately recognized after 2 months with a 100% TAR @ 0.1% FAR using 3000 ppi. Conversely, 1000 ppi scanners failed to capture fine details in young children's fingerprints, indicating the necessity for more specialized technology. We also found that 500 ppi was adequate for children older than 4 years when the time gap between enrollment and authentication was one year. The 3000 ppi contactless scanner demonstrated superior

performance in young children and outperformed 1000 ppi contact-based scanners on a large scale for both verification and identification. Yet, for older children, its performance was comparable to 500 ppi. One limitation of our study is the relatively small dataset of young children, suggesting the need for further research to validate our findings for this demographic. Future work will involve collecting more longitudinal data from additional subjects and examining factors like age at enrollment, demography, the time gap between enrollment and authentication, and image quality, using the Linear Mixed Effect model to understand their impact on match scores. We also plan to analyze the data for various time gaps and break down the 4-15 years age group into individual age groups to better understand the time gap's impact within each specific age group.

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