A. Brömme, N. Damer, M. Gomez-Barrero, K. Raja, C. Rathgeb,
A. Sequeira, M. Todisco, and A. Uhl (Eds.): BIOSIG 2022,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2022

Fundamental Study of Neonate Fingerprint Recognition Using Fingerprint Classification

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Abstract: UNICEF reported that many of the 2.4 million deaths within 28 days of birth were preventable with appropriate vaccination. There are several reasons why babies cannot be vaccinated, for example, the medical staff does not have appropriate vaccination history management to control who and when they should be vaccinated. To properly manage vaccination history and promote its widespread use, personal identification after birth is essential, and a neonate fingerprint identification technology could be one of the solutions. In this paper, we develop a fingerprint scanner with a 2,674ppi high-resolution CMOS sensor specifically designed to acquire neonatal fingerprints by integrating positive comments from users in the research field on the previous prototype. We also propose a neonate fingerprint identification method based on fingerprint classification.

Keywords: Fingerprint recognition, Neonate fingerprint, Fingerprint scanner, Pattern classification.

1 Introduction

According to the UNICEF report [Un21], more than 5 million children died before the age of five in 2022 alone, even not including the increased mortality rate attributable to COVID-19, and much of this loss of life could have been prevented. In particular, half of the deaths, 2.4 million, occurred during the neonatal period, that is, the first 28 days of life. The United Nations has stated its aim to "provide legal identity to all, including birth registration," in the Sustainable Development Goals (SDGs), target 16.9. One of the significant collaborative effects of this goal is the reduction of under-five mortality, which is listed in target 3.2 as "By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as

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low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births [Un15].” While many cases can be prevented through proper vaccination, there are several problems in delivering vaccines to babies. Among them, problems of budgeting for vaccines, operations, and logistics including delivery costs, can be supported by global organizations that assist developing countries. However, even if such organizations can deliver vaccines to rural areas in developing countries, the critical problem remains as to when and to whom medical staffs need to provide vaccines under the appropriate controlled procedure. This problem can be addressed by providing a vaccination history management system with identifying infants, including neonates. The use of biometrics is the first choice for personal authentication in this system, because of its advantage that anyone can prove his or her identity without verbal explanation or presentation of an identification document. This advantage should be extended to the youngest generation, the neonates, to reduce the tragedies occurring in the world today.

The use of features such as fingerprints, iris, and ears has been considered for biometric recognition of babies [Mo21]. Among them, fingerprint recognition [Ma03], which is widely used in government including national ID, has been studied. Fingerprint recognition should be available immediately after birth to manage vaccination history, however, most research has focused on the age group of infants [KHJ16, Ja17, Mo21, En22]. Koda et al. [Ko19] developed a 2,400 ppi fingerprint scanner and succeeded in acquiring fingerprint images of a neonate at two hours of birth. On the other hand, the acquired fingerprint image is not always available for fingerprint recognition since the fingerprint image is unclear because of video capturing. This paper develops a fingerprint scanner for acquiring images from neonatal fingerprints. This scanner consists of a 2,674 ppi CMOS sensor and can capture images of $1,920 \times 1,080$ pixels at 30fps. The scanner can be connected via a general-purpose USB driver, allowing users to use it in any environment. We demonstrate in this paper that we have successfully captured clear fingerprint images of neonates during the first two hours of life using this scanner. In many cases such as National ID systems, fingerprint recognition methods based on minutia matching [KHJ16, Ja17] or CNNs that extract minutia features [En22] are used. Fingerprint images acquired from neonates have large sweat pores and thin ridges, preventing the use of minutiae-based methods. On the other hand, the flow of ridges, which is a global fingerprint feature, can be confirmed, and thus we propose a fingerprint recognition method for neonates based on fingerprint classification using deep learning. We demonstrate the effectiveness of the proposed method through experiments using a dataset of neonate fingerprint images collected by the developed fingerprint scanner.

2 Fingerprint Scanner for Newborns

In this section, we describe the fingerprint scanner that we developed in this paper, which can obtain fingerprint images from neonates only a few hours after birth.

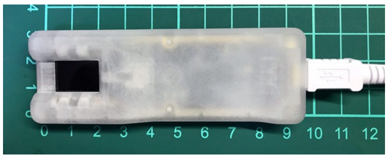

Fig. 1: Our 2,674 ppi neonate fingerprint scanner.

2.1 History of Newborn Fingerprint Scanner Development

The development of a newborn fingerprint scanner has started in 2015. At the beginning of its development in 2015, the fingerprint scanner was mainly designed with a 1,270 ppi CMOS sensor with 20μm pitch elements adopting a global shutter and a ϕ12 μm FOP (Fiber Optic Plate) for image enhancement using the SLDR method described in Koda et al. [KHJ16], to confirm the resolution required to capture images from the skin surface of neonate fingers. The first prototype successfully collected fingerprint images of newborns after six hours in an experiment in India conducted by Michigan State University [Ja16].

Since 2018 we have changed our research field to Kenya. In this study, two models of the updated prototype were used. The first model consists of a fingerprint scanner with a 1,270ppi sensor and physical guides around the sensor to limit the sensing area preventing misplacement of the finger and elastic deformation of the target finger of the baby by strong pressure. At the onsite research in 2019, this model worked, reducing the cases of misplacement (cases of two fingers on a single image did not occur) and elastic deformations. This result adequately demonstrates the positive effects of the physical guides. The second model consists of a fingerprint scanner with a 2,400 ppi CMOS sensor with 10μm pitch elements adopting a global shutter and a ϕ12 μm FOP [KHJ16], This model was designed with the resolution required to capture fingerprint images of the babies soon after the birth, and also has a mode to collect in a video image to confirm the deformation of the fingerprint at the time of capture. It is necessary to address the typical case of discharge of a newborn within 6 hours of birth. We successfully acquired fingerprint images of a newborn at 2 hours after birth in the evaluation of this model in 2019. From this onsite research, we determined the resolution required to collect the newborn fingerprints [Ko19]. The sensor resolution required for collecting fingerprints from newborns was also mentioned by Moolla et al. [Mo21] who stated that fingerprint scanners that can capture images with a resolution of 2,400 ppi or higher are required to collect fingerprint images from very small fingers of babies.

This 2,400 ppi scanner can automatically capture video images at 7fps, however, it needs to be designed for easier use. In addition, no-image data areas occurred at the beginning and end of the recorded video images, resulting in many FTAs (Failure to Acquire). To reduce FTAs and operate data collection properly, the data collected by this model required a very large amount of computing resources before using the data for identification, and the plan for updating the data collection mechanism was very complex. After several months of field research, volunteer medical professionals strongly requested that the 2,400 ppi scanner should be updated to capture still images, with a mechanical switch on the back of the scanner and a physical guide on the sensing area, as well as the 1,270 ppi scanner.

Even after receiving valuable feedback from the site, research activities were restricted during the impact of COVID-19, from 2020 to the end of 2021. As a result, we could not contact volunteer babies to collect the data required for updating the scanner. This lack of opportunity caused significant delays in our research.

2.2 Latest Newborn Fingerprint Scanner Development

We resumed the onsite research in the beginning of 2022 to confirm the capabilities of the latest prototype. Fingerprint images were collected from neonates in a developing country through an onsite research from March 25 to April 26, 2022. The latest prototype consists of a 2,674 ppi CMOS sensor with 9.5μm pitch elements adopting a rolling shutter and a $\phi 12$ μm FOP, which can capture images with $1,920 \times 1,080$ pixels even from a sensing area surrounded by a physical guide as shown in Fig. 1.

There are 2 major updates to this latest model, described in the following. The first is to implement a CMOS sensor with a rolling shutter. A CMOS sensor with a global shutter can acquire images more consistently, although it is more expensive than a CMOS sensor with a rolling shutter. In developing countries, the cost of procurement is one of the key factors, not the availability of brand new technology. Therefore, the latest model adopts a rolling shutter CMOS sensor, which is a Commercial Off-The-Shelf (COTS) product that exceeds 30 fps, to achieve stable image processing during capturing.

The second is to provide a driverless (plug-and-play) mode. It is necessary to reduce the complexity of the setup at the time of installation, considering the operation in the medical field in developing countries. In the previous prototype, at least two drivers had to be installed to control the scanner. Therefore, this installation process was discouraged by medical staff who were not good at using computers.

From the above, the specifications of the latest prototype is designed to implement a 2,674 ppi CMOS sensor with rolling shutter capable to capture 1,920$\times$1,080-pixel images at 30fps, runs without the driver installation process, has a body size of 930mm (D) $\times$320mm (W) $\times$13mm (H), and is less than 30g in weight.

3 New Findings of Neonate Fingerprints

Although some information on the baby's fingerprint itself was obtained from previous studies such as [Ko19], understanding the delivery procedure at the maternal facility is necessary to understand the skin condition of the baby's fingertips as they are affected by the delivery. Our new findings through the onsite study are discussed below.

We confirmed the latest situation in the initial treatment of neonates in medical facilities through discussions with several medical staffs, including physicians, through the on-site study. We found that the dry-technique policy and strategy recommended by WHO make it difficult to clean the hands by bathing. The WHO stated that “Do not wipe off the vernix” and “Do not bathe the baby during first 24 hours of life” [Wo14]. This manner is currently widespread in developed countries and is recommended in developing countries as well. It was difficult to collect fingerprint images by wiping the fingertips under these circumstances. As shown in Fig. 2, only low-quality fingerprint images could be collected from the fingertips of babies with vernix and sebum.

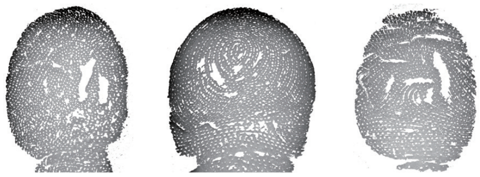

Fig. 2: Examples of fingerprint images with sebum and vernix.

As a fundamental investigation to realize neonate fingerprint recognition under such circumstances, we evaluate the fingerprint image quality using fingerprint images collected from 82 neonates in the on-site study. We collected auxiliary information: (i) estimated date of delivery (EDD), (ii) date of birth (DOB), and (iii) birth weight, simultaneously with fingerprint images. For 21 of the 82 neonates, information of EDD and weight was not available due to inadequate maternal health care. We analyze the relationship between auxiliary information and fingerprint quality for the 61 newborns whose auxiliary information was available. We predicted that neonates with lower body weights would result in poorer quality fingerprint images due to their smaller body size and skin area. Table. 1 shows a summary of the analysis results. We use the image quality criterion as to whether the fingerprint image can be manually classified from the ridge pattern, that is, we assume that the image quality is high if the fingerprint image can be classified since it is difficult to apply general fingerprint image quality evaluation methods to neonate fingerprint images. The difference between EDD and DOB, which is indicated by “Gap,” and body weight are used as metrics in the analysis. Note that a negative value of Gap indicates preterm birth. While there was no significant relationship between body weight and image quality, there was a clear relationship between Gap and image quality. The lower image quality of the fingerprint images indicated a mean Gap of approximately -18.64 days, indicating a preterm birth. The low-quality fingerprint images include the earliest cases born more than 30 days before EDD. We understood that we need to identify neonates even under the case of delivery at 9 months of gestation found in the above.

Tab. 1: Relationship between image quality and auxiliary information. The image quality is assumed to be high if the fingerprint image can be manually classified. “Gap” indicates the difference between EDD and DOB and a negative value indicates a preterm birth.

Image quality	# of neonates	Gap [days]	Body weight [kg]
Low	11	-18.64	3.05
High	50	-0.54	2.74

We investigate whether preterm delivery has any influence on the formation of fingerprints. We confirm the process of fingerprint formation during the fetal period, especially the beginning and end of ridge formation. Fingerprints are developed in two phases: primary ridge and secondary ridge. The primary ridge is the actual ridge configuration of the volar skin surface and begins to develop around 10 weeks after fertilization. From 17 to 24 weeks, the secondary ridge continues to grow to a comparable site on the skin surface relative to the primary ridge, finally developing into the same adult morphology as the epidermal ridge pattern by 24 weeks [Wi91]. The beginning of ridge formation is mentioned in several papers, but the end of fingerprint ridge formation could not be found, except for web information from an Indian maternal clinic[Cl]. This site shows that the fingerprint ridge pattern begins to appear during fetal development and becomes a unique pattern by the end of 9 months. If this information is scientifically accepted, it will be very valuable. Therefore, it is necessary to match fingerprint images collected from all neonates, including those born prematurely at less than 9 months of gestation, to develop neonate fingerprint recognition techniques.

4 Neonate Fingerprint Classification

Through the above on-site study, we found that many fingerprint images obtained from neonates are of low quality due to dry technique and preterm birth. As shown in Fig. 2, an unwiped fingerprint image has many sebum and vernix that have filled the valley lines, making it difficult to extract minutiae using conventional minutia matching methods. Therefore, we need to develop a new method to identify newborns using fingerprint images acquired under the dry method or those of preterm neonates. In this paper, we propose a neonate fingerprint recognition method using multiple fingerprint image classifications, utilizing the fact that ridge patterns are visible even in neonate fingerprint images of low image quality. Fingerprint image classification is of course unsuitable for large-scale identification. One of the requests from medical staff at the hospital where the onsite study was conducted is the identification of babies at the time of discharge from the hospital. At that hospital, there are around 1,000 deliveries per year. If the registered fingerprint pattern sequences among the three babies for each birthday are not the same, fingerprint pattern classification can be utilized as a method of matching neonates.

We consider classifying fingerprint images acquired from four fingerprints (left thumb, left index finger, right thumb, and right index finger) into five classes: Arch (A), Double loop (D), Left loop (L), Right loop (R), and Whorl (W). As an initial investigation of neonate fingerprint recognition, we propose a method for classifying neonate fingerprint images based on ResNet-18 [He16], which is one of the most widely used CNN models in image classification. To take a grayscale image as input, the first convolution layer of ResNet-18 is changed to a 1-channel input. We also add an adaptive average pooling layer, batch normalization, dropout, a fully-connected layer, batch normalization, and a fully-connected layer after ResNet-18.

5 Experiments and Discussion

We describe an experiment to evaluate the performance of the proposed method using neonate fingerprint images acquired in the on-site study. Our dataset consists of a training dataset of 1,357 images, a validation dataset of 166 images, and a test dataset of 1,181 images collected from 82 subjects. Note that the test dataset consists of fingerprint images taken from neonates that differ from the training and validation datasets. We manually labeled each image with one of the following six classes: Arch (A), Double loop (D), Left Loop (L), Right Loop (R), Whorl (W), and Unknown (U). The three loops are defined using the information on the direction of the ridge flow and the location of the starting point. For example, a right loop is defined as an image with a pattern that starts on the right side and climbs to the center of the finger while going toward the left side. The image that could not be manually identified by any of the patterns is categorized as U. Fingerprint images from the 82 babies in the test dataset were collected over one month, excluding five days of religious holidays. All babies delivered during a research period have been discharged from a hospital within a day after birth. It needs to declare that to confirm the performance, this experiment needs to include not only the cases of normal delivery but also the cases of special delivery such as cesarean sections however, no cases of cesarean sections and multiple births were found during this period. Fig. 3 shows examples of fingerprint images in the test dataset. The ID shown in the figure corresponds to Table. 1. The time shown in parentheses indicates the time since birth. ID 4 and ID 2 are examples of fingerprint images with high image quality, ID 21 and ID 73 are examples of fingerprint images that can be classified but have low image quality, and ID 32 and ID 1 are examples of fingerprint images with low image quality that cannot be classified. Regarding unclassified images exampled at the above, as a supplementary explanation, a baby as ID 32 born on 4 days later the EDD is the case having negative effect of the dry technique policy and a baby as ID 1 born on 32 days prior the EDD is the case having negative effect of the preterm birth.

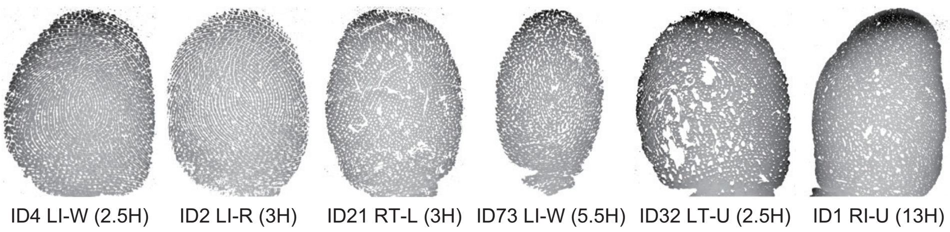

Fig. 3: Examples of fingerprint images in the test dataset. The time shown in parentheses indicates the time since birth. ID 4 and ID 2 are examples of fingerprint images with high image quality, ID 21 and ID 73 are examples of fingerprint images that can be classified but have low image quality, and ID 32 and ID 1 are examples of fingerprint images with low image quality that cannot be classified.

Table. 1 shows the class labels of the 328 fingerprint images collected from the four fingers (RT, RI, LT, LI) of 82 babies. We exclude 27 fingers of 16 babies from the evaluation since they were classified as U based on the low quality of the fingerprint images. Finally, fingerprint images of 301 fingers from 82 babies are used for evaluating the classification accuracy. Note that there is one pair of babies born on the same date (April 21 in Table. 1) with the same fingerprint pattern sequence. This means that we can assume that only about 1% of the babies with the same fingerprint sequence on the same day will be registered. This case is marked with a bold square as shown in Table. 1. From this table, we can consider that a combination of fingerprint classification patterns can be used to identify neonates. However, we need to consider the use and removal of unclassifiable fingerprints and the case where the fingerprint pattern sequences of babies born on the same day are the same. Therefore, in practice, one solution is to combine the information of the guardian as the primary identification method and identify the registered neonate with the guardian's data.

We describe the experimental conditions of the proposed method. ResNet-18 used in the proposed method is a pre-trained model on ImageNet. We perform fine tuning of the proposed method using the training dataset described above. Since the acquired fingerprint image includes the second joint, only the fingerprint region is cropped. If the size is less than $1,216 \times 1,216$ pixels, the image is padded with white color, otherwise, the center of the image is cropped to $1,216 \times 1,216$ pixels. The image is then resized to 224×224 pixels and used as the input image. The number of training data is increased by a factor of 4, i.e., 5,428 images, using data augmentation such as random flip, random distortion, and random noise. The loss function is Cross Entropy, the batch size is 16, the optimization function is RMSProp, and the learning rate is 0.001. As shown in Table. 2, the experimental results using the proposed method demonstrate that 236 fingers are classified into the same class as manual classification, where the fingers correctly classified by the proposed method are indicated by the light red background. 65 classification errors by the proposed method are indicated with black backgrounds. The accuracy of the proposed method is 78.4% of that of manual classification. As a result, we plan to improve the accuracy of our method and begin a feasibility study for automatic and real-time person authentication using fingerprint pattern classification information.

6 Conclusion

In this paper, we developed a 2,674 ppi fingerprint scanner for acquiring fingerprint images from neonates within a few hours of birth. Using this scanner, we have successfully obtained clear fingerprint images from neonates at about two hours of birth. Through our on-site study, we found that minutiae were difficult to extract due to the dry technique as recommended by the non-wiping treatment policy after delivery and insufficient fingerprint forming due to preterm delivery at 9 months' gestation. Therefore, we proposed a neonate fingerprint recognition method based on fingerprint image classification. We demonstrated the effectiveness of the proposed method through experiments on a test dataset consisting of 82 neonates. As a result, we considered that one-to-one (or one-to-few) matching using fingerprint pattern classification of babies and identification of their guardians could be used for antenatal and postnatal management at medical facilities and vaccination candidate checking on the day of immunization. We have launched the world's first feasibility study of using the classification information of fingerprint images as one of the neonate's identifiers in a short time from birth to discharge from the hospital. Since the neonatal

Tab. 2: Summary of fingerprint information in the test dataset.

ID	Clasiffication	Left Thumb	Left Index	Right Thumb	Right Index	DOB
1	Manual	W	U	D	U	26-Mar-22
	ResNet18	W		**W**		
2	Manual	A	R	A	R	
	ResNet18	A	R	A	R	
3	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
4	Manual	W	W	W	W	
	ResNet18	W	W	W	W	
5	Manual	W	R	W	L	
	ResNet18	W	**W**	W	L	
6	Manual	R	R	L	R	
	ResNet18	R	R	L	R	
7	Manual	R	W	W	W	
	ResNet18	R	W	W	W	
8	Manual	W	W	D	A	27-Mar-22
	ResNet18	W	W	**W**	**L**	
9	Manual	R	W	L	L	
	ResNet18	**D**	W	L	L	
10	Manual	D	R	L	L	
	ResNet18	D	R	**A**	L	
11	Manual	D	W	D	W	
	ResNet18	W	W	**W**	W	
12	Manual	W	L	D	R	
	ResNet18	W	L	D	R	
13	Manual	A	A	A	A	
	ResNet18	A	A	A	A	
14	Manual	U	R	U	L	28-Mar-22
	ResNet18		R		L	
15	Manual	R	R	D	W	
	ResNet18	R	R	**W**	W	
16	Manual	W	R	L	L	
	ResNet18	W	R	**R**	L	
17	Manual	D	R	W	A	29-Mar-22
	ResNet18	**W**	**A**	W	A	
18	Manual	A	R	U	L	
	ResNet18	A	R		L	
19	Manual	D	R	W	L	30-Mar-22
	ResNet18	**W**	R	W	L	
20	Manual	D	A	D	D	
	ResNet18	**R**	**L**	**W**	**L**	
21	Manual	R	W	L	L	
	ResNet18	R	W	L	L	
22	Manual	R	U	U	U	31-Mar-22
	ResNet18	R				
23	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
24	Manual	R	R	L	L	1-Apr-22
	ResNet18	R	R	L	L	
25	Manual	A	R	D	W	
	ResNet18	A	**R**	**W**	**R**	
26	Manual	A	L	A	L	
	ResNet18	A	**R**	A	**W**	
27	Manual	W	W	W	W	
	ResNet18	W	W	W	W	
28	Manual	A	A	L	A	
	ResNet18	A	A	L	**L**	
29	Manual	W	R	W	W	2-Apr-22
	ResNet18	W	R	W	W	
30	Manual	U	R	U	L	
	ResNet18		R		L	
31	Manual	R	L	L	L	3-Apr-22
	ResNet18	R	L	**A**	L	
32	Manual	U	R	L	U	
	ResNet18		R	L		
33	Manual	D	R	A	L	
	ResNet18	D	R	A	L	
34	Manual	D	A	D	L	
	ResNet18	D	A	**W**	**A**	
35	Manual	D	R	W	W	
	ResNet18	**W**	R	W	W	
36	Manual	D	L	W	W	
	ResNet18	**W**	**W**	W	W	
37	Manual	W	W	W	L	
	ResNet18	**D**	W	W	L	
38	Manual	W	U	W	U	
	ResNet18	W		W		
39	Manual	W	R	W	L	4-Apr-22
	ResNet18	W	R	W	L	
40	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
41	Manual	W	L	W	R	5-Apr-22
	ResNet18	W	L	W	**W**	
42	Manual	U	W	L	W	
	ResNet18		W	**W**	W	
43	Manual	D	R	D	L	
	ResNet18	**R**	R	**W**	L	
44	Manual	A	D	A	L	
	ResNet18	A	**W**	A	L	
45	Manual	W	R	W	L	6-Apr-22
	ResNet18	**R**	R	**A**	L	
46	Manual	R	R	W	L	
	ResNet18	R	R	W	L	
47	Manual	D	W	L	W	7-Apr-22
	ResNet18	**L**	W	**W**	W	
48	Manual	R	R	L	L	8-Apr-22
	ResNet18	R	R	L	L	
49	Manual	W	A	W	L	9-Apr-22
	ResNet18	W	**R**	W	L	
50	Manual	R	L	W	L	
	ResNet18	R	L	W	L	
51	Manual	D	R	W	W	10-Apr-22
	ResNet18	D	R	W	W	
52	Manual	D	R	D	W	
	ResNet18	**W**	R	D	W	
53	Manual	D	W	L	W	
	ResNet18	**W**	W	L	W	
54	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
55	Manual	W	W	W	W	
	ResNet18	W	W	W	W	
56	Manual	U	W	W	W	11-Apr-22
	ResNet18		W	W	W	
57	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
58	Manual	U	A	L	L	
	ResNet18		**L**	L	L	
59	Manual	R	W	L	W	
	ResNet18	R	W	L	W	
60	Manual	R	A	L	R	
	ResNet18	R	**L**	L	R	
61	Manual	R	W	L	L	12-Apr-22
	ResNet18	R	W	L	L	
62	Manual	A	R	L	L	
	ResNet18	A	R	L	L	
63	Manual	W	W	W	R	
	ResNet18	**D**	W	**A**	R	
64	Manual	W	W	W	W	13-Apr-22
	ResNet18	W	W	W	W	
65	Manual	U	R	W	L	14-Apr-22
	ResNet18		R	W	L	
66	Manual	R	R	D	L	20-Apr-22
	ResNet18	**A**	**A**	**W**	L	
67	Manual	R	L	U	U	
	ResNet18	R	L			
68	Manual	R	R	D	L	
	ResNet18	**L**	R	**W**	L	
69	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
70	Manual	R	R	L	L	21-Apr-22
	ResNet18	R	R	L	L	
71	Manual	R	A	L	L	
	ResNet18	R	**R**	L	L	
72	Manual	U	W	U	L	22-Apr-22
	ResNet18		W		L	
73	Manual	U	W	U	U	
	ResNet18		**A**			
74	Manual	W	W	W	W	
	ResNet18	**D**	W	W	W	
75	Manual	U	R	W	W	23-Apr-22
	ResNet18		**A**	W	**R**	
76	Manual	R	R	L	L	
	ResNet18	R	R	L	L	
77	Manual	W	W	W	W	24-Apr-22
	ResNet18	**D**	W	**D**	W	
78	Manual	R	R	U	L	
	ResNet18	R	R		L	
79	Manual	D	W	L	D	
	ResNet18	**W**	W	L	**W**	
80	Manual	W	W	W	R	25-Apr-22
	ResNet18	**L**	**L**	**L**	R	
81	Manual	W	W	W	W	
	ResNet18	**D**	**A**	**D**	W	
82	Manual	R	R	L	L	
	ResNet18	R	R	L	L	

period is the first stage of providing legal identity to all, we plan to improve the sensor and the neonatal fingerprint identification method, and also consider combining this method with the conventional minutiae-based fingerprint recognition method.

7 Acknowledgement

Authors hereby declare that the parents or guardians of babies who join this research were properly requested to sign onto a consent form as a permission of their participation for this research. This research is appropriately approved by Scientific Ethics Review Unit (SERU) of Kenya Medical Research Institute (KEMRI) before data collection.The author(s) disclose the receipt of the extraordinary on-site assistance for the research of this article from supporters in Kenya and we hereby express our gratitude for Kwale county government, Kenya, NUITM-KEMRI project office in Kenya of Nagasaki University Institute of Tropical Medicine, and The Center for Microbiology Research, KEMRI, and the Director General, KEMRI.

References

[Cl] Cloudnine hospitals: , When does your baby develop fingerprint in your womb? `https://www.cloudninecare.com/blog/when-does-your-baby-develop-fingerprints-in-your-womb`. Accessed on 14 May, 2022.

[En22] Engelsma, J. J.; Deb, D.; Cao, K.; Bhatnagar, A.; Sudhish, P. S.; Jain, A. K.: Infant-ID: Fingerprints for Global Good. IEEE Trans. Pattern Analysis and Machine Intelligence, 44(7):3543–3559, July 2022.

[He16] He, K.; Zhang, X.; Ren, S.; Sun, J.: Deep Residual Learning for Image Recognition. Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 770–778, June 2016.

[Ja16] Jain, A. K.; Arora, S. S.; Best-Rowden, L.; Cao, K.; Sudhish, P. S.; Bhatnagar, A.; Koda, Y.: Giving Infants an Identity: Fingerprint Sensing and Recognition. Proc. 8th Int'l Conf. Information and Communication Technologies and Development, pp. 1–4, June 2016.

[Ja17] Jain, A. K.; Arora, S. S.; Cao, K.; Best-Rowden, L.; Bhatnagar, A.: Fingerprint Recognition of Young Children. IEEE Trans. Information Forensics and Security, 12(7):1501–1514, July 2017.

[KHJ16] Koda, Y.; Higuchi, T.; Jain, A. K.: Advances in capturing child fingerprints: A high resolution CMOS image sensor with SLDR method. Proc. 15th Int'l Conf. Biometrics Special Interest Group, pp. 329–336, September 2016.

[Ko19] Koda, Y.; Takahashi, A.; Ito, Koichi; Aoki, T.; Kaneko, S.; Nzou, S. M.: Development of 2,400ppi Fingerprint Sensor for Capturing Neonate Fingerprint within 24 Hours after Birth. Proc. 18th Int'l Conf. Biometrics Special Interest Group, pp. 95–106, September 2019.

[Ma03] Maltoni, D.; Maio, D.; Jain, A. K.; Prabhakar, S.: Handbook of Fingerprint Recognition. Springer, 2003.

[Mo21] Moolla, Y.; De Kock, A.; Mabuza-Hocquet, G.; Ntshangase, C. S.; Nelufule, N.; Khanyile, P.: Biometric Recognition of Infants using Fingerprint, Iris, and Ear Biometrics. IEEE Access, 9:38269–38286, February 2021.

[Un15] United Nations: General assembly 15-15900 (E). United Nations, September 2015.

[Un21] United Nations Children's Fund: Levels & trends in child mortality report 2021. United Nations Children's Fund, December 2021.

[Wi91] William, J. Babler: Embryologic development of epidermal ridges and their configurations. Birth Defects, 27:95–112, February 1991.

[Wo14] World Health Organization: Early Essential Newborn Care Clinical practice pocket guide. World Health Organization, October 2014.