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Research Article

Multi-Instance Contingent Fusion for the Verification of Infant Fingerprints

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It is imperative to establish an automated system for the identification of neonates (1–28 days old) and infants (29 days–12 months old) through the utilisation of the readily accessible 500 ppi fingerprint reader. This measure is crucial in addressing the issue of newborn swapping, facilitating the identification of missing children, monitoring immunisation records, maintaining comprehensive medical history, and other related purposes. The objective of this study is to demonstrate the potential for future identification of infants using fingerprints obtained from a 500 ppi fingerprint reader by employing a fusion technique that combines multiple instances of fingerprints, specifically the left thumb and right index fingers. The fingerprints were acquired from babies who were between the ages of one day and six months at the enrolment session. The sum-score fusion algorithm was implemented. The approach mentioned above yielded verification accuracies of 73.8%, 69.05%, and 57.14% for time intervals of 1 month, 3 months, and 6 months, respectively, between the enrolment and query fingerprints.

1. Introduction

The objective of Target #16.9 within the sustainable development goals (SDGs) established by the United Nations is to ensure universal access to legal identification, including birth registration, by the year 2030. The facilitation of accurate birth registration would enable the provision of comprehensive identification documentation, thus ensuring the establishment of a lifelong identity for all individuals. In developing nations, the prevailing method of birth registration involves the utilisation of paper-based birth certificates, which are susceptible to several vulnerabilities such as forgery, misplacement, and theft [1].

The utilisation of biometrics, which involves the measurement of an individual's physiological or behavioural characteristics, has the potential for the automation of birth registration processes [2]. The use of automated birth registration systems offers a range of benefits, including establishing a lifelong identity for individuals, facilitating the identification of missing children, monitoring vaccination coverage, and maintaining comprehensive medical history records.

Biometrics present an effective and dependable approach to addressing specific facets of identity management through the utilisation of fully automated or semiautomated systems that identify persons based on their inherent physical and/or behavioural characteristics [3]. Identifying and verifying children with biometric technology is an emerging field of study. Biometric characteristics, including facial features, fingerprints, palm prints, footprints, iris patterns, ear shapes, and ball prints, have been utilised to identify children across different age ranges [4–25]. However, the identification of neonates and infants aged 1 day to 6 months remains an unresolved research domain.

The selection of a biometric characteristic for a particular application is influenced by several key factors, including the distinctiveness and durability of the characteristic, its prevalence within the intended population, the feasibility of collecting the characteristic, the effectiveness of the system, the acceptance of the system by users (representing the target population), the susceptibility to potential threats, and the integration of the system with other components [26]. Table 1 presents the supplementary factors that should be considered when selecting a biometric characteristic to identify children. An overview of the table indicates that fingerprint recognition is the most appropriate biometric characteristic for identifying neonates and infants [28].

This study aims to verify the identity of neonates and infants using 500 ppi fingerprints. A multi-instance, contingent fusion of the child's left thumb and right index finger was used to accomplish this.

The fingerprint images were obtained from babies in the immunisation clinic of the Government Hospital in Ota, Ogun State, Nigeria, per their immunisation schedule. This method might potentially be employed to monitor the administration of vaccines to children. This study was conducted to show that 500 ppi fingerprints acquired at 0–3 months old can be used to verify the identity of children as they age.

2. Materials and Methods

2.1. Covenant University Neonate and Infant Fingerprint (CU-NIF) Database. This database contains the fingerprints of 250 neonates (1–28 days old) and infants (29 days—10 months old), including both males and females. The fingerprints were obtained using the Digital Persona U.are.U 4500 fingerprint reader at the immunisation clinic of the State Hospital, Ota, Ogun State, Nigeria. The Covenant University Health and Research Ethics Committee (CHREC) and hospital administrators approved the data collection.

2.2. Fingerprint Acquisition. The acquisition of fingerprints was conducted for three (3) sessions, with a time interval ranging from 1 to 7 months between each session. The fingerprint scanner used for this purpose was the Digital Persona U.are.U 4500, which has a resolution of 500 ppi. A total of four samples were obtained for each of the left and right, thumb, and index fingers. Before acquisition, the fingers were cleaned using a dry cloth. The babies experienced little to no discomfort throughout the fingerprinting process, and the fingerprint scanner was "cleaned" with adhesive tape following each baby's session. The acquisition process of the fingerprint reader was limited by the automatic capture mode, as it only allowed for viewing of the fingerprint images after they had been captured, rather than during the acquisition. Consequently, the presence of low-quality images necessitated the recapture of the fingerprint image, resulting in an increase in the acquisition throughput.

In three sessions from January 2020 to September 2020, 250 babies' left and right thumbs and index fingers were acquired. In the initial session (enrolment), the infants' ages varied from one day to ten months. The interval between each session varied from 4 weeks to 7 months. A total of 135 male and 115 female babies participated. A total of 147 participants exclusively attended Session 1, while 61 persons exclusively attended both sessions 1 and 2. In addition, only 42 participants were present for all three sessions. During each session, a total of four (4) samples were collected from the left and right thumb and index fingers of all infants, except for 13 infants. These 13 infants had fewer than four samples taken for certain fingers due to either restlessness or unsuccessful fingerprint enrolment. On average, it took 3 minutes to get the fingerprints of each participant. The study participants' parents or guardians were provided with a comprehensive explanation of the research and the procedure for obtaining fingerprints. They were then requested to provide their informed consent by voluntarily signing a consent form before the capture of their babies' fingerprints. Obtaining the fingerprints of the infants posed a challenge because of the inadvertent lack of cooperation from the participants. Consequently, measures were taken to ensure the participants' hands remained still to get high-quality fingerprint images. Furthermore, a subset of individuals was unable to provide the necessary 16 fingerprint samples due to factors such as restlessness or distress, resulting in incomplete data collection. Some randomly selected samples of the acquired fingerprint images are shown in Figures 1 and 2.

2.3. Experimental Protocol. The algorithm receives the enrolment and query images of the left thumb (I_{LE} and I_{LQ}, respectively). The minutiae extractor, MINDTCT, extracts the minutiae $((x_{\mathrm{LE}}, y_{\mathrm{LE}}, \theta_{\mathrm{LE}}), (x_{\mathrm{LQ}}, y_{\mathrm{LQ}}, \theta_{\mathrm{LQ}}))$ from the enrolment and query images, respectively, and the matcher, BOZORTH3, compares the minutiae of the enrolment and query images $((x_{\mathrm{LE}}, y_{\mathrm{LE}}, \theta_{\mathrm{LE}}), (x_{\mathrm{LQ}}, y_{\mathrm{LQ}}, \theta_{\mathrm{LQ}}))$ to obtain a match score, σ_L. If σ_L is equal to or higher than the predetermined threshold τ, the participant's identity is deemed genuine, and the procedure concludes. If σ_L is lower than τ, the algorithm is provided with the enrolment and query images of the right index finger ($I_{\mathrm{RE}}, I_{\mathrm{RQ}}$). The minutiae extractor, MINDTCT, extracts the minutiae $((x_{\mathrm{RE}}, y_{\mathrm{RE}}, \theta_{\mathrm{RE}}), (x_{\mathrm{RQ}}, y_{\mathrm{RQ}}, \theta_{\mathrm{RQ}}))$ from the enrolment and query images, respectively, and the matcher, BOZORTH3, compares the minutiae of the enrolment and query images $((x_{\mathrm{RE}}, y_{\mathrm{RE}}, \theta_{\mathrm{RE}}), (x_{\mathrm{RQ}}, y_{\mathrm{RQ}}, \theta_{\mathrm{RQ}}))$ to obtain a match score, σ_R. If σ_R exceeds or equals the predetermined threshold, τ, the participant's identity is deemed genuine, and the verification process is concluded. If σ_R is lower than τ, the fusion of σ_L and σ_R is performed using sum score fusion. If the combined score, σ_F, is equal to or greater than the predetermined threshold τ, the participant will be deemed eligible for acceptance. If the combined score, σ_F, is below the predetermined level, τ, the participant will be deemed an imposter. The flowchart and algorithm depicting the procedure are illustrated in Figure 3 and provided below, respectively.

Table 1: Supplementary factors to be considered in the selection of a biometric trait for identifying children [27].

Biometric trait	Ease of capture (challenges)	Intraclass variation	Parental concerns	Dataset availability	Applications
Face	Easy (variation in illumination and expression, closed eyes)	Large (due to craniofacial morphology)	Minor	Not available in the public domain	Identification documents and surveillance
Fingerprint	Relatively easy	Increase in the ridge structure of the fingers	Moderate	Not available in the public domain	Forensics, national identification, and immigration
Iris	Difficult (closed eyes, crying)	None	Major (intrusive capture)	Not available in the public domain	Immigration, national identification and refugee identification
Palmprint	Difficult (closed fist, concavity of the palm)	Increase in the size of the palm	Moderate	Not available in the public domain	Same as that of fingerprints

Figure 1: The fingerprints of a subject at 2 months, 3 months, and 9 months old, respectively.

Figure 2: The fingerprints of a subject at 1 week, 7 weeks, and 5 months old, respectively.

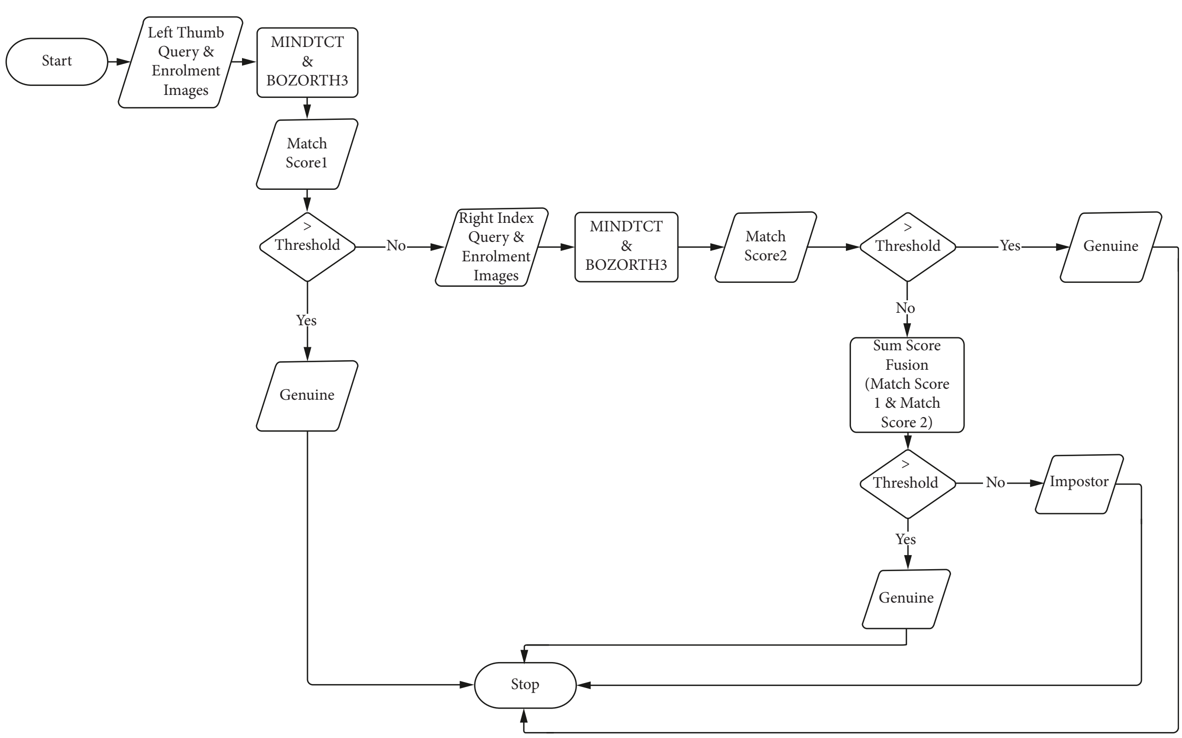

Figure 3: Flowchart of multi-instance contingent fusion for the verification of infant fingerprints.

Input: $I_{\mathrm{LE}}, I_{\mathrm{LQ}}, I_{\mathrm{RE}}, I_{\mathrm{RQ}}$
Output: $\sigma_L, \sigma_R, \sigma_F$
Initialisation: $\tau \leftarrow 40$
MINDTCT $(I_{\mathrm{LE}}) \leftarrow (x_{\mathrm{LE}}, y_{\mathrm{LE}}, \theta_{\mathrm{LE}})$
MINDTCT $(I_{\mathrm{LQ}}) \leftarrow (x_{\mathrm{LQ}}, y_{\mathrm{LQ}}, \theta_{\mathrm{LQ}})$
BOZORTH3 $((x_{\mathrm{LE}}, y_{\mathrm{LE}}, \theta_{\mathrm{LE}}), (x_{\mathrm{LQ}}, y_{\mathrm{LQ}}, \theta_{\mathrm{LQ}})) \leftarrow \sigma_L$
if $\sigma_L \geq \tau$ **then**
    Genuine/Accept ▷ The identity is verified
else if $\sigma_L < \tau$ **then**
    MINDTCT $(I_{\mathrm{RE}}) \leftarrow (x_{\mathrm{RE}}, y_{\mathrm{RE}}, \theta_{\mathrm{RE}})$
    MINDTCT $(I_{\mathrm{RQ}}) \leftarrow (x_{\mathrm{RQ}}, y_{\mathrm{RQ}}, \theta_{\mathrm{RQ}})$
    BOZORTH3 $((x_{\mathrm{RE}}, y_{\mathrm{RE}}, \theta_{\mathrm{RE}}), (x_{\mathrm{RQ}}, y_{\mathrm{RQ}}, \theta_{\mathrm{RQ}})) \leftarrow \sigma_R$
    if $\sigma_R \geq \tau$ **then**
        Genuine/Accept ▷ The identity is verified
    else if $\sigma_R < \tau$ **then**
        $\sigma_F \leftarrow \sum(\sigma_L, \sigma_R)$
        if $\sigma_F \geq \tau$ **then**
            Genuine/Accept ▷ The identity is verified
        else if $\sigma_F < \tau$ **then**
            Imposter/Reject ▷ The identity is not verified
        end if
    end if
end if

Algorithm 1: Multi-instance contingent fusion for infant fingerprint verification [27].

The purpose of this study was achieved by utilising the left thumb (LT) and right index (RI) fingers of the participants who were present in all three sessions. A total of six experiments were conducted.

Experiment 1: The fingerprints of the left thumb and right index finger obtained in the first session (S1) were designated as the enrolment images, whereas the fingerprints of the left thumb and right index finger obtained in the second session (S2) were used as the query images.

Experiment 2: The images used for enrolment consisted of the left thumb and right index fingerprints obtained in the second session (S2). The query images, on the other hand, were obtained from the left thumb and right index fingerprints acquired in the third session (S3).

Experiment 3: The purpose of this experiment was to investigate the feasibility of utilising fingerprints obtained from infants under three months old as a means of verifying their identity when they reach three months of age. This investigation was prompted by the significant time gap between the first and third sessions.

Experiment 4: The match scores acquired from the subjects' left thumb and right index fingers, whose identities were unverifiable in Experiment 1, were combined using the sum score fusion method.

Experiment 5: The match scores of the left thumb and right index fingers of the participants, whose identities could not be verified in Experiment 2, were subjected to sum score fusion.

Experiment 6: The purpose of this experiment was to investigate whether fusion would enhance the verification rate of Experiment 3.

3. Results and Discussion

The process involved the extraction of fingerprint minutiae with the National Institute of Standards and Technology (NIST) feature extractor, MINDTCT, and subsequent comparison of the extracted minutiae with the NIST matcher, BOZORTH3. The accuracy of the unimodal verification was found to be low, consistent with previous findings published in the literature. The integration of match scores from multiple instances in the verification process significantly improved the accuracy of verification. The sum-score fusion approach was employed to combine the match scores due to its effectiveness in fusing genuine scores from multiple tests [29].

3.1. Experiment 1. The purpose of this experiment was to assess the verification accuracy of infant fingerprints when there was an average time interval of one month between the query and enrolment fingerprints. A verification accuracy of 34.1% was achieved with an equal error rate (EER) of 0.2983, as shown in Figure 4, while the area under the receiver operating characteristic curve (AUC-ROC) presented in Figure 5 was computed to be 0.776925.

3.2. Experiment 2. The purpose of this experiment was to assess the accuracy of infant fingerprint verification when there was an average time interval of 3 months between the

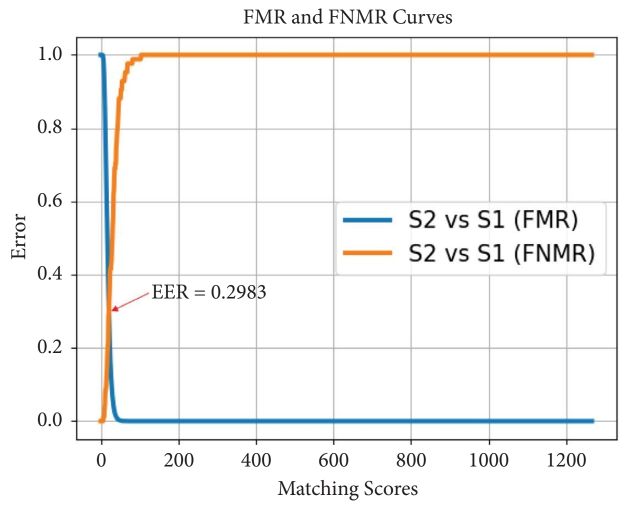

Figure 4: EER of Experiment 1. The EER is the point at which false match rate (FMR) equals false nonmatch rate (FNMR).

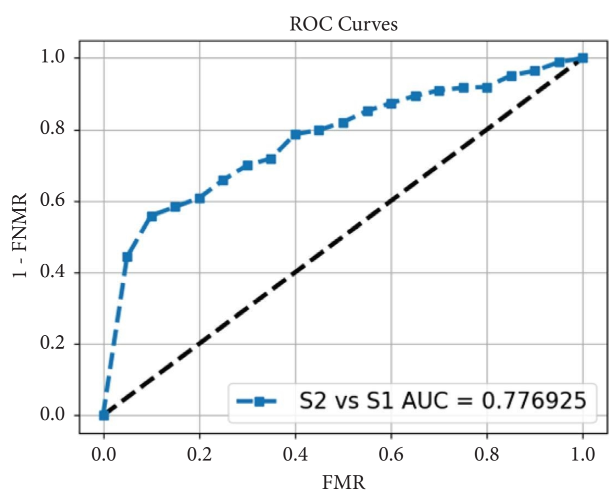

Figure 5: ROC curve of Experiment 1.

query and enrolment fingerprints. A verification accuracy of 35.71% was achieved with an EER of 0.3003, as shown in Figure 6, while the AUC-ROC in Figure 7 was computed to be 0.761160.

3.3. Experiment 3. The purpose of this experiment was to assess the verification performance of infant fingerprints when there was an average time interval of 6 months between the query and enrolment fingerprints. The verification accuracy was 11.9% with an EER of 0.3426, as shown in Figure 8, and Figure 9 shows that the AUC-ROC value was 0.681872.

3.4. Experiment 4. The purpose of this experiment was to assess the impact of sum score fusion on the verification accuracy of Experiment 1. The contingent fusion method was employed to combine the match scores of the left thumb and right index fingerprints for participants whose identities

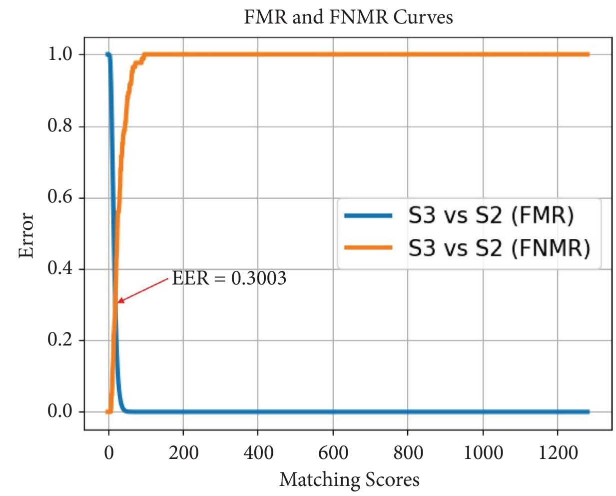

Figure 6: EER of Experiment 2.

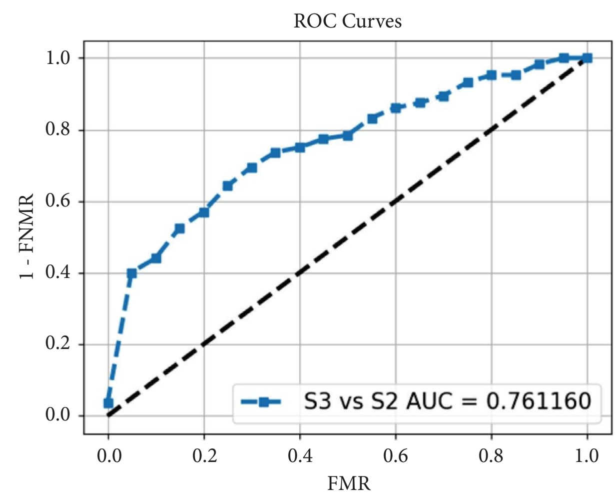

Figure 7: ROC curve of Experiment 2.

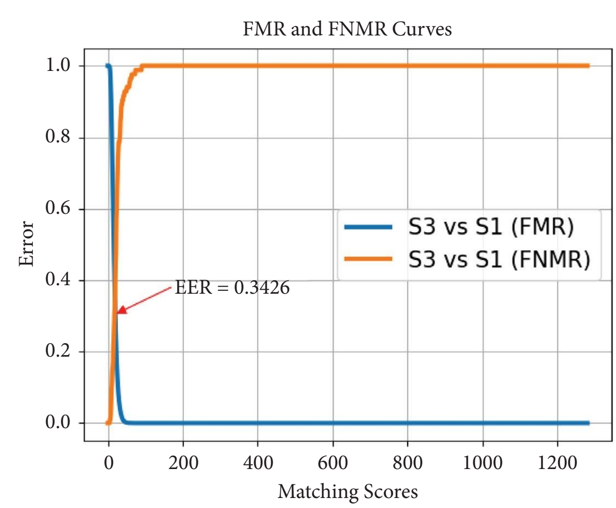

Figure 8: EER of Experiment 3.

could not be verified in Experiment 1. There was a notable improvement in verification accuracy, which rose from 34.1% to 73.8%. The EER is 0.2700, as shown in Figure 10.

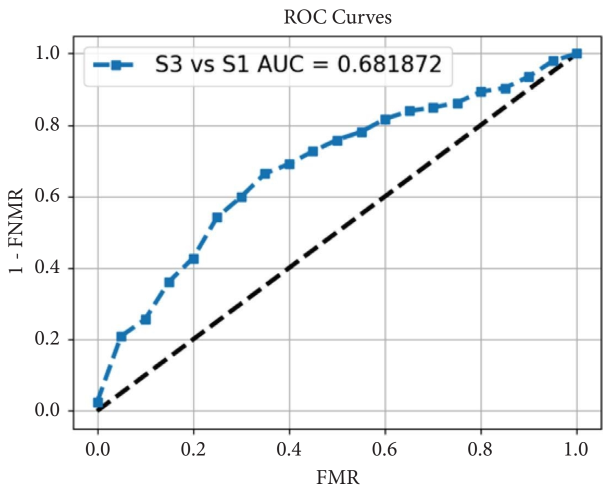

Figure 9: ROC curve of Experiment 3.

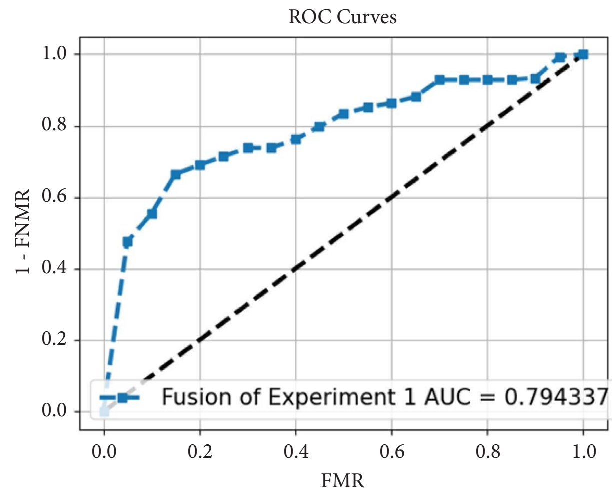

Figure 11: ROC curve of Experiment 4.

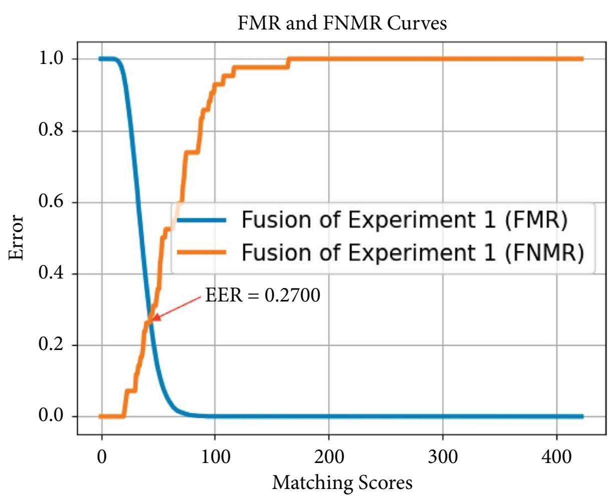

Figure 10: EER of Experiment 4.

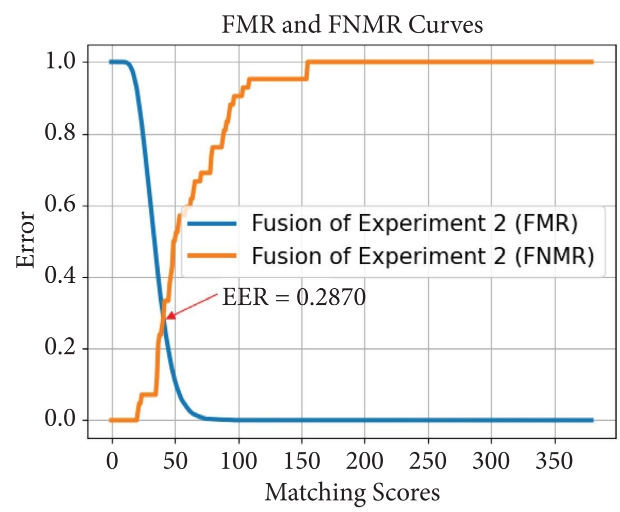

Figure 12: EER of Experiment 5.

Figure 11 shows that the area under the receiver operating characteristic curve (AUC-ROC) was computed to be 0.794337.

3.5. Experiment 5. The purpose of this experiment was to assess the impact of sum score fusion on the verification accuracy of Experiment 2. The contingent fusion method was employed to combine the match scores of the left thumb and right index fingerprints for participants whose identities could not be verified in Experiment 2. There was an improvement in verification accuracy from 35.71% to 69.05%. The EER is 0.2870, as shown in Figure 12. The results depicted in Figure 13 demonstrate that the area under the receiver operating characteristic curve (AUC-ROC) was computed to be 0.803351.

3.6. Experiment 6. The purpose of this experiment was to assess the impact of sum score fusion on the verification accuracy of Experiment 3. The contingent fusion method was employed to combine the match scores of the left thumb and right index fingerprints for participants whose identities could not be verified in Experiment 3. The verification accuracy improved from 11.9% to 57.14%, and the EER is 0.3396, as shown in Figure 14, and Figure 15 shows that the AUC-ROC was computed to be 0.696175.

The enhanced verification accuracies achieved in Experiments 4, 5, and 6, as demonstrated in Table 2, indicate that a greater time interval between the query and enrolment images necessitates fusion.

The experimental results indicate that it is possible to authenticate the identities of infants aged 6 months and above by utilising 500 ppi fingerprints obtained before the age of 6 months. This can be achieved by fusing the match scores of multiple instances of two or more uncorrelated fingerprints. In addition, the results demonstrate that the utilisation of contingent sum score fusion resulted in improved verification accuracy.

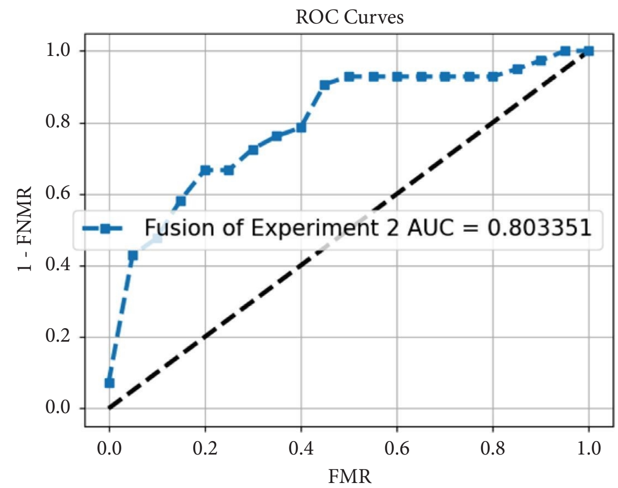

Figure 13: ROC curve of Experiment 5.

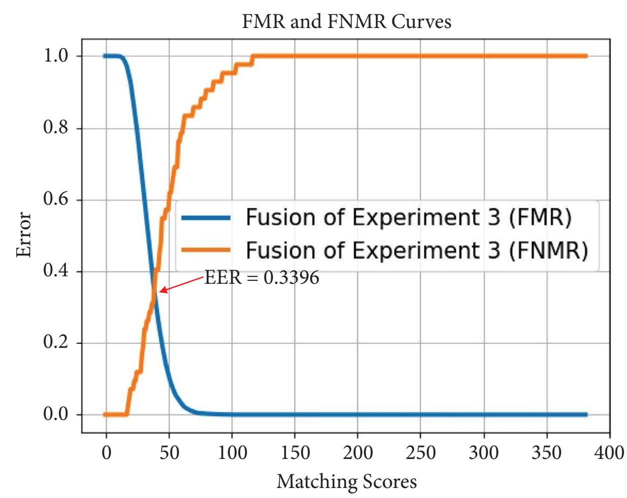

Figure 14: EER of Experiment 6.

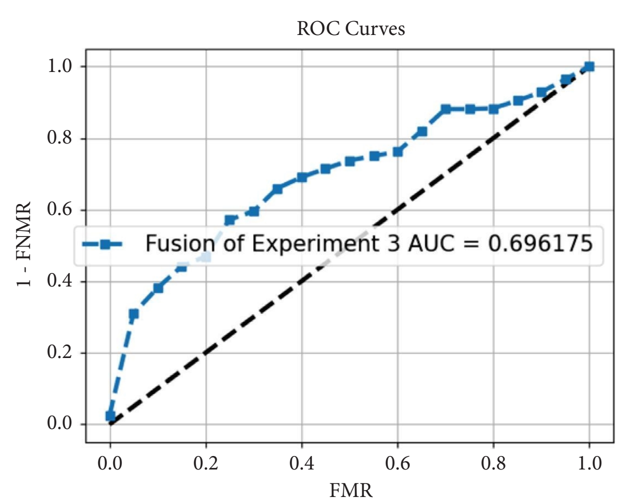

Figure 15: ROC curve of Experiment 6.

Table 2: Prefusion and postfusion verification accuracies.

Experiment	Mode	Time interval (month)	Verification accuracy (%)
Experiment 1	LT/RI	1	34.1
Experiment 2	LT/RI	3	35.71
Experiment 3	LT/RI	6	11.9
Experiment 4	Fusion of LT and RI	1	73.8
Experiment 5	Fusion of LT and RI	3	69.05
Experiment 6	Fusion of LT and RI	6	57.14

Table 3: Benchmarking the results of this study with extant studies that used 500 ppi fingerprint images.

Methodology	Age at enrolment (months)	Verification accuracy (%)
Multisample and multi-instance fusion [30]	0–3	65.8 (after 3 months)
[31]	0-1	1.25
	1-2	7.57
	2-3	15.61
Multialgorithm, multisample, and multi-instance fusion [32]	0-1	0
	1-2	35.5
	2-3	52.1
Multi-instance contingent fusion (this study)	1–4	69.05 (after 3 months)

As shown in Table 3, in comparison with existing literature [30–32], this study achieved a verification accuracy of 69.05% for infants enrolled between 1 and 4 months old and verified after 3 months.

4. Conclusions

This study made significant contributions to the existing body of knowledge with the creation of the first African infant fingerprint dataset, acquired with a 500 ppi fingerprint reader, that will be available on an Open Access basis under creative commons licence to advance research in infant fingerprint recognition and the development of a multi-instance contingent fusion algorithm for the verification of infant fingerprints. The results of this study demonstrate that using multi-instance contingent fusion to fuse the match scores of infant fingerprints can result in an improvement in the accuracy of the identity verification process. This can be adopted to verify the identity of infants in tracking vaccinations and maintaining a medical history. The absence of ancillary information in the participant's informed consent form, which could have been used to incorporate soft biometrics and improve the verification accuracy of the system, limited the scope of this study.

Data Availability

The Covenant University Neonate and Infant Fingerprints (CU-NIF) data used to support the findings of this study are restricted by the Covenant University Health Research Ethics Committee (CHREC) to protect the identity of the participants. Data are available from Tiwalade Odu, tiwalade.odu@covenantuniversity.edu.ng, for researchers who meet the criteria for access to confidential data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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