A Hybrid Model by Combining Discrete Cosine Transform and Deep Learning for Children Fingerprint Identification

Vaishali Kamble[1], Manisha Dale[2], Vinayak Bairagi[3]
Department of Electronics and Telecommunication, AISSMS Institute of Information Technology, Pune[1]
Department of Electronics and Telecommunication, Modern Education Society's College of Engineering, Pune, India[1]
Department of Electronics and Telecommunication, Modern Education Society's College of Engineering, Pune, India[2]
Department of Electronics and Telecommunication, AISSMS Institute of Information Technology, Pune[3]

***Abstract*—Fingerprint biometric as an identification tool for children recognition was started in the late 19th century by Sir Galton. However, it is still not matured for children as adult fingerprint identification even after the span of two centuries. There is an increasing need for biometric identification of children because more than one million children are missing every year as per the report of International Centre of missing and exploited children. This paper presents a robust method of children identification by combining Discrete Cosine Transform (DCT) features and machine learning classifiers with Deep learning algorithms. The handcrafted features of fingerprint are extracted using DCT coefficient's mid and high frequency bands. Gaussian Naïve Base (GNB) classifier is best fitted among machine learning classifiers to find the match score between training and testing images. Further, the Transfer learning model is used to extract the deep features and to get the identification score. To make the model robust and accurate score level fusion of both the models is performed. The proposed model is validated on two publicly available fingerprint databases of children named as CMBD and NITG databases and it is compared with state-of-the-art methods. The rank-1 identification accuracy obtained with the proposed method is 99 %, which is remarkable compared to the literature.**

Keywords*—Discrete Cosine Transform (DCT); Curve DCT; biometric recognition; machine learning; convolutional neural network; AlexNet

I. Introduction

Children missing, swapping and abduction is caused due to non-recognition of them from their faces or other biometrics as they are in the developing stage in this age. The rate of mishaps happening to them is increasing day by day due to non-availability of the authentic system for recognition of them. Researchers studied the different biometrics like face [1,2,3,4], palmprint [5], footprint [6], ear [7] and headprints [8] for recognition of children.

Fingerprint modality is most widely used biometric for recognition of adults. Dr. Faulds [9] used fingerprints for identification of persons in 1870. As per Sir Galton theory, the fingerprint similarity chance in two different persons is 1 in 64 billion [10]. In children, the fingerprints show distinctive features which can differentiate them from others, though they are in the developing stage.

Fingerprint recognition can be done by two methods: minutiae matching and pattern matching. Minutiae are small details in fingerprints like ridge, valley, ridge ending, bifurcation. In minutiae matching, different minutiae are matched against each other and the highest match probability is considered as the correct match. The problem with minutia match for children recognition is biometric aging. The displacement of minutiae points due to growth in fingers. One needs a growth model to recognise the longitudinal (after time lapse) fingerprint images of children. The second method of pattern matching is based on the texture of fingerprint images. Fingerprint images are rich in texture and hence frequency domain representation is suited for it. The basic block diagram of fingerprint recognition is as shown in Fig. 1. Original fingerprint is processed and enhanced to get the most suitable features. The features are extracted using the feature extraction algorithms. These features are stored as feature vectors in the training process. The test phase is similar up to feature extraction, then these features are compared with stored features with the help of a matching algorithm or by using a classifier. The estimated match with the test image is the output of the identification system.

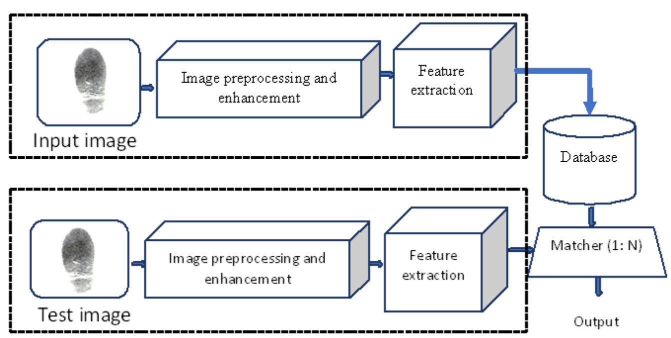


Fig. 1. Basic block diagram of image identification

A. Literature Review

Automatic recognition of children using fingerprints was first studied by Jain et al. [11] in 2014 to increase the coverage of vaccination for the age group of 0 to 4 years. They used the up-sampling process by a factor of 1.8 to match the finger ridge distance to adults. Camacho et al. [12] also proposed a solution of up-sampling the fingerprint by an interpolation factor based on children's ridge distance. Preciozzi et al. [13] formulated a scale factor based on distance between the ridges of adults to the distance between ridges of an age of child. By using these scale factors, the verification accuracy of children's fingerprints increases. Haraksim et al. [14] computed fingerprint minutiae-based growth model to reduce the biometric aging result on children recognition

Further, the hardware implementation of the fingerprint systems is also done to verify the accuracy of the fingerprints recognition. Koda et al. [15], designed the high resolution (1270 ppi) fingerprint scanner for scanning the minute details of children's fingerprints. Kalisky et al. [16] also designed high resolution platen free optical scanner. Engelsma et al. [17] studied the infants of 0 to 3 months to reduce the mortality of infants. They used a 1900 ppi scanner to capture the details of the infant's fingerprint. Improvement in the accuracy is observed by increasing resolution of the scanner. Macharia et al. [18] showed the Android based system for recognition of children and discussed the fingerprint quality of children. Engelsma et. al. [19] further studied the problem of recognition of children for vaccination and nutritional supply with the 1900 ppi RaspiReader designed by him.

Most of the researchers used Commercial Software Defined Kits (SDK) for the recognition of children [20,21]. Jain et al. [22] continued his research in children recognition and this time collected the longitudinal database of infants. CNN is used for improving the quality of images. Feature extraction and matching is done with Commercial SDK. The longitudinal study is continued by Jain et. al [23] for children verification. They used an Automatic fingerprint recognition system for feature extraction and matching. Engelsma et. al. [19] extracted features using a texture based Convolutional Neural Network (CNN) matcher with two Commercial off the shelf matchers (COTS). Patil et. al. [24] designed a fingerprint recognition system for infants and toddlers by extracting the finger codes by Gabor filtering and matching them using Euclidean distance. Moolla et al [25] investigated for the best modality for infants' recognition among fingerprint, iris and ear. The Research done in children fingerprint recognition is very less. The publicly available databases of children's fingerprints are also less. It is observed that feature extraction and matching of children's fingerprints is majorly done using commercial recognition systems. In latest research CNN and COTS systems are studied and are combined to achieve high accuracy. Transform based features are rarely studied for the biometrics of children. Fingerprint image is rich in frequency domain features therefore transform domain features should be derived.

In this paper, we are proposing a hybrid model of children fingerprint recognition by combining identification scores of DCT features with GNB classifier and CNN. As seen from Fig. 1 fingerprints of children are tiny as compared to adult fingerprints. Finding Minutia from such images is a difficult task. Finding the frequency domain features will integrate minutia and other texture features. The structure of fingerprints of two different people are shown in Fig. 2. The frequency related to each area is shown in it. The most dissimilar portion needs to separate out from the fingerprint image. This portion is the mid to high frequency core area of the fingerprint.

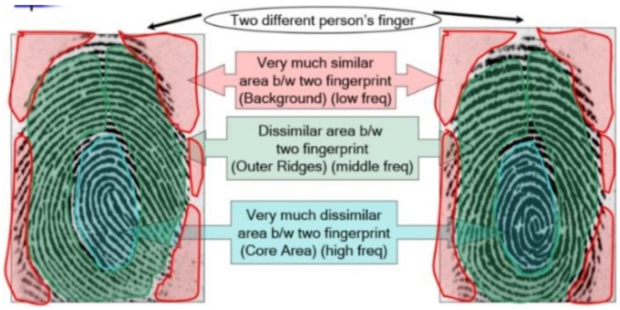


Fig. 2. Frequency distribution in fingerprint image.

The DCT has strong ability to remove correlation between the pixels like KL transform [26]. DCT allows selection of the bands directly in the frequency. Hence, we are proposing a hybrid model in which scores of classifiers GNB and CNN on the feature extracted using DCT and texture features of CNN are combined.

The contributions of research are:

- Studied transform and texture features of fingerprints for recognition of children.
- Combined Transform domain features with Machine Learning approach.
- Score level fusion of traditional method and deep learning method.
- Identification of children for this age group is studied for the first time in the literature.

The sections of the paper include Introduction, which elaborate the basic blocks and need of fingerprint recognition of children; methodology, which gives an overall idea of methods used in the proposed algorithm. Experimental Results gives information about the database used and results of different approaches. Finally, the conclusion and future scope gives insight on findings of the experimentation and future direction of study.

II. Methodology

In this hybrid method, transform domain approaches combined with machine learning are presented and it gives promising results. The different approaches of experimentations are carried as follows:

a) DCT, Curve DCT feature extraction (Standard Deviation) and Canberra distance for feature matching is used.

b) DCT, Curve DCT used to calculate standard deviation and these features are classified using machine learning classifiers.

c) Transfer learning AlexNet model [27] used to compare with the transform domain approach.

d) The Score level fusion of Transform domain approach and Transfer learning approach is done using Max Rule, Sum Rule and Product Rule. The workflow of the research is elaborated in Fig. 3.

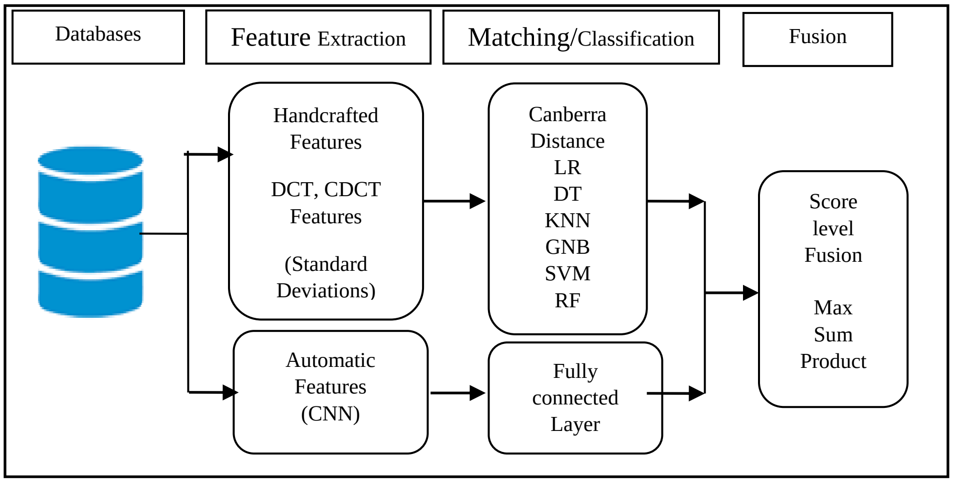


Fig. 3. Work flow of the research

A. Image Enhancement and ROI Extraction

Children's fingerprints are difficult to capture and captured fingerprints are not clear. It cannot be used directly for any algorithm. Fingerprint pre-processing and enhancement plays a crucial role in the recognition process. The most dissimilar portion shown in Fig. 2 needs to separate out from the fingerprint image. This portion is the high frequency core area of the fingerprint. To separate out the high (discriminative) frequency portion, the enhancement [28] and ROI extraction [29] steps are elaborated below.

1) Image normalisation and segmentation: First an input fingerprint image is normalized using mean M0 = 100 and variance V AR0 = 100. The fingerprint is normalised with the help equation 1. After normalising the image segmentation is done. The standard deviation is calculated of the segmented region.

The Normalized image is defined as:

$$G\,(l,\mathrm{m}) = \begin{cases} M0 + \sqrt{\frac{VAR0\,(I(l,m)-M)^2}{VAR}}\ , \ if\ I(il,m) > M \\ M0 - \sqrt{\frac{VAR0\,(I(l,m)-M)^2}{VAR}},\ otherwise, \end{cases} \tag{1}$$

Where, I(l, m) are gray level values at pixel(l, m), M and VAR are estimated mean and variance of I, G (l, m) is normalized Gray-level value at pixel (l, m) , M0 and VAR0 are the desired mean and variance values.

2) Local orientation estimation: The normalized fingerprint image is used for the orientation estimation. The local ridge orientation at (l;m) is computed using eq. (2). The local ridge orientation is given in eq. (2).

$$O(l,m) = \frac{1}{2}\tan\frac{\phi'_y(l,m)}{\phi'_x(l,m)} \tag{2}$$

Where, $\phi'_{x,}\ \phi'_y$ is image vector for lowpass filtering θ (l, m) is the least square estimate of the local ridge orientation at the block centred at pixel (l, m).

3) Local frequency estimation: The local frequency is estimated using normalized and estimated orientation image. It is given in eq. (3).

$$F(l,\mathrm{m}) = \sum_{u=\frac{-\omega\Omega}{2}}^{\frac{w_l}{2}} \sum_{v=\frac{-\omega\Omega}{2}}^{\frac{w_l}{2}} W_l\ \ (u,v)\Omega'\,(\mathrm{l\ -uw}),\ (\mathrm{m\text{- }vw}) \tag{3}$$

Where, w_l is a two-dimensional low pass filter with unit length. w_l = 7 is the size of the filter. Ω' = interpolated frequency

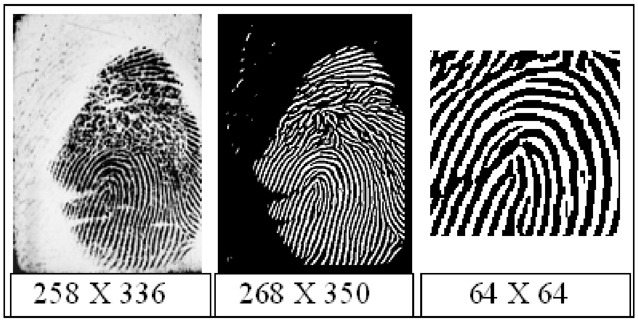
4) Mask estimation: Normalized image is pixelwise divided into recoverable or an unrecoverable part depending upon local ridges and valleys. The three characteristics for each part are calculated, which are differences between the mean value of peak and mean value of valley. Second is the mean number of pixels between two peaks and third is the variance of the local part. These characteristics are used to classify the image in recoverable or an unrecoverable part.

5) Filtering: A bank of Gabor filters used as bandpass filters to remove the noise. These filters are tuned with orientation and frequency of local parts. The final enhanced image is obtained using eq. (4).

$$E\,(i,j) = \begin{cases} 255,\ \ if\ R(i,j) = 0 \\ \sum_{u=-{w_g}/_2}^{{w_g}/_2} \sum_{v=-{w_g}/_2}^{{w_g}/_2} \mathrm{h}(u,v:\ O(i,j)\,,\ F(i,\ j))G(i-u)(j-v), \\ otherwise \end{cases} \tag{4}$$

Where, G = normalized fingerprint images, O = orientation image, F = frequency image, R = recoverable mask, where w_g = 11 gives the size of the Gabor filters.

6) ROI extraction: In the enhanced image the core point is detected using slope technique as described in paper [take from email of madam]. The original image, enhanced image and ROI extracted image is shown in Fig. 4.



(a) (b) (c)

Fig. 4. (a) Original image, (b) Enhanced image, (c) ROI of enhanced image.

B. Feature Extraction

Fingerprint texture consists of repetitive patterns of pixel intensities and it is unique to every person. To extract the texture features (standard deviations) from fingerprint images DCT, CurveDCT are applied to the ROI of fingerprint images.

1) DCT: DCT is one of the most used transforms for image compression, feature extraction and recognition. The important properties of DCT are decorrelation, energy compaction and fast implementation. These properties are explored for the fingerprint feature extraction. The 2D- DCT of an image f(x, y) is given in eq. (5). The size of the image is M X N. Variations of MN are U = 0 to M-1 V = 0 to N-1.

$$T(u,v) = \frac{1}{\sqrt{MN}}\, CuCv \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x.y)\cos\left(\frac{(2x+1)u\pi}{2M}\right) cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (5)$$

The ROI is divided into four non-overlapping parts as shown in Fig. 5. The DCT is applied to each part, from each part 9 standard deviations are derived by grouping different frequency coefficients as shown in Fig. 6. Here low frequency coefficients are omitted as fingerprint image is mid and high frequency texture image as shown in Fig. 2. Total 36 features are extracted from four parts of the finger. Training is done with 4 images and average standard deviation is stored as a feature vector. Partitioning of the image gives better energy compaction and decorrelation. The mean and standard deviation is calculated from the eq. (6) and (7).

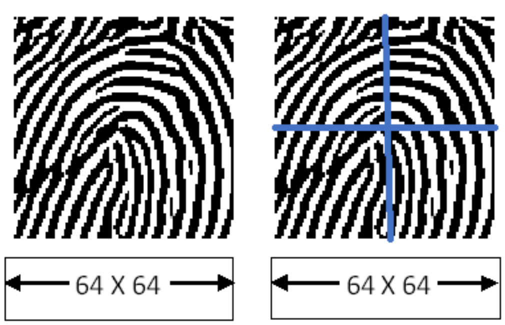


Fig. 5. (a) ROI (b) ROI is divided in four parts

The mean (m) and standard deviation (sd) is calculated from the eq. (6) and (7).

$$(m) = \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j) \quad (6)$$

$$(sd) = \sqrt{\frac{1}{N^2}\sum_{j,j=1}^{N}[p(i,j) - m]^2} \quad (7)$$

Thus, the total features are 36 X 500 = 18000 derived from the DCT standard deviation of the images from the database.

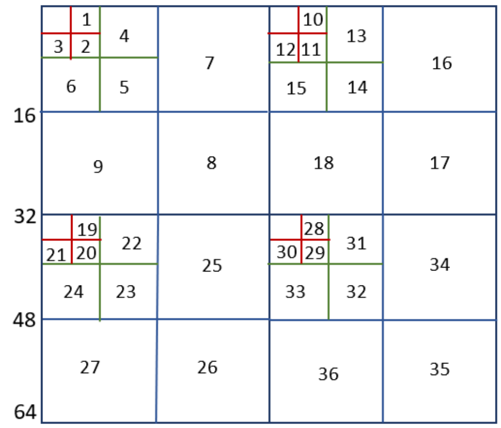


Fig. 6. DCT blocks of fingerprint image

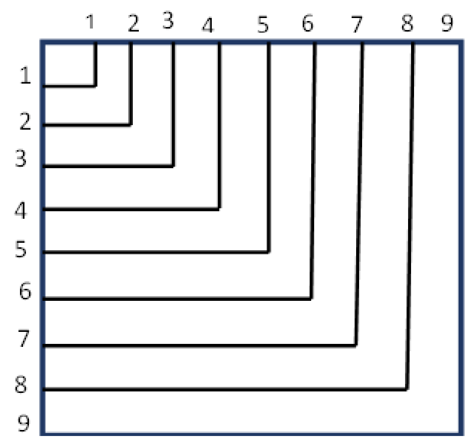


Fig. 7. Curvature bands of coefficients

2) Curve-DCT (CDCT)

First fingerprint image is divided as shown in Fig. 5, into four parts. For every part, 2D-DCT transform is applied and coefficients are grouped in 9 bands in a curvature manner as shown in Fig. 7. Looking at the distribution from top left corner to right bottom corner of the coefficients and their grouping, curvature form is more appropriate. For every band standard deviation is calculated. Total 36 features from four parts are stored as a training dataset.

C. Evaluation Parameters

Evaluation of the experiments is done with class-wise identification accuracy. It is shown in eq. (8).

$$\text{Class-wise identification accuracy} = \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i} \quad (8)$$

The tp_i is i^{th} true positive, tn_i is i^{th} true negative, fn_i is i^{th} false negative, fp_i is i^{th} false positive where i ranges from 1 to 100.

The CMC curves are used to show the Rank wise accuracy of the fusion models. Rank 1 accuracy is the accuracy achieved when the outcome is the same as ground truth at the first match by model. It can also be called as top 1 accuracy.

III. Experimental Results

A. Children Fingerprint Database

There are several fingerprint databases such as MSU-ITF, VaxTrac, CMBD [30] and NITG [24,31] of the children's fingerprints. Most of the databases are not available due to security reasons except Children's Multimodal Biometric Database (CMBD) of IIIT Delhi and National Institute of Technology, Goa (NITG) database for research purposes. In this work CMBD and NITG databases are used. Total 1000 images of the left thumb from both the databases and 100 subjects from each database are used for experimentation. Both the databases used Slap fingerprint scanner with 500 ppi resolution. Some sample images of these databases are shown in Fig. 8.

Fig. 8. (a) Right thumb, (b) left thumb of CMBD [30] and (c) Right thumb (d) left thumb of NITG database [24,31]

The performance of DCT domain features is checked for children's fingerprints. The DCT is applied on cropped fingerprint images and standard deviation is calculated for a group of DCT coefficients. In the first experiment, after grouping of coefficients is done in two ways as explained in section 2.2.1 and 2.2.2. The recognition rate in identification mode is calculated using Canberra distance. This distance is normalized as seen from the eq. (8), and it is giving better accuracy than Euclidean distance. The Canberra distance between vectors a and b is in the eq. (9).

$$d(a,b) = \sum_{i=1}^{n} \frac{|ai-bi|}{|ai+bi|} \qquad (9)$$

The recognition rate obtained is shown in Table I. The maximum recognition rate (RR) is obtained with DCT features and using a simple distance classifier for 100 subjects is 63 % for the train test split of 80-20.

TABLE I. Recognition Rate (RR) with DCT, CDCT Features and Canberra Distance for Classification on CMBD and NITG Databases

Features	RR for CMBD	RR for NITG
DCT	42	63
CDCT	29	37

This recognition rate (RR) is less and to improve upon it, the same feature set is given to machine learning classifiers in the next experiment. Machine learning (ML) Supervised learning classifiers are used for classification of labeled databases of children's fingerprints. These classifiers learn on their own classification of objects/images depending upon the data/features presented at the input. As machine learning are data driven models, it analyses input features, learns from it and gives the classification [32]. Choosing the best ML classifier for an application depends on the data set available, the number of features derived, data is labelled or not, variance of features etc. In this experiment the same DCT and CDCT features are given to the different classifiers such as Logistic Regression (LR), Decision Tree (DT), K- Nearest Neighbour (KNN), Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM) and Random Forest (RF). In image classification not only the features of the images but also the classification algorithms play a crucial role. The recognition rate after applying the different classifiers to the DCT, CDCT feature set is shown in Table II. As seen from the table, results obtained with CDCT features and GNB classifiers show significant improvement as compared to the first experiment. Gaussian Naïve Bayes is a Generative classifier. It requires a smaller number of parameters for classification. This classifier is probability based, where conditional and prior probabilities are calculated using Maximum Likelihood Estimation [33].

In the third experiment, the Neural Network approach is tested. As the database is small, a pre-trained AlexNet model is used for classification. Here the ROI of fingerprint image is resized to 200 X 200. Total images are split in 80-20 for training and testing. The Optimizer used is Stochastic Gradient Descent and the loss function is Sparse Categorical Cross Entropy. The recognition accuracy of AlexNet is shown in Table III for both the databases. The results obtained for CMBD database with both approaches are comparable but for NITG database DCT features and machine learning approach gives better results. Model accuracy and model loss of AlexNet approach on both the databases is shown in Fig. 9 and 10.

TABLE II. DCT AND CDCT FEATURES (STANDARD DEVIATION) EXTRACTION AND MACHINE LEARNING CLASSIFIERS ON CMBD AND NITG DATABASES

Recognition rate of CMBD database on ML classifiers						
Feature Extractor	LR	DT	KNN	GNB	SVM	RF
DCT	34.1	68.8	27.5	83.3	11.6	47
CDCT	29	71	19	92	10	44
Recognition rate of NITG database on ML classifiers						
Feature Extractor	LR	DT	KNN	GNB	SVM	RF
DCT	52.8	66.4	36.4	81.6	33.6	61
CDCT	36	66	25	96	22	45

TABLE III. COMPARISON OF PROPOSED METHOD WITH ALEXNET

Methods	NITG (100)		CMBD (100)	
AleNet	Model Accuracy	Model Loss	Model Accuracy	Model Loss
	88 %	0.5350	92 %	0.3975

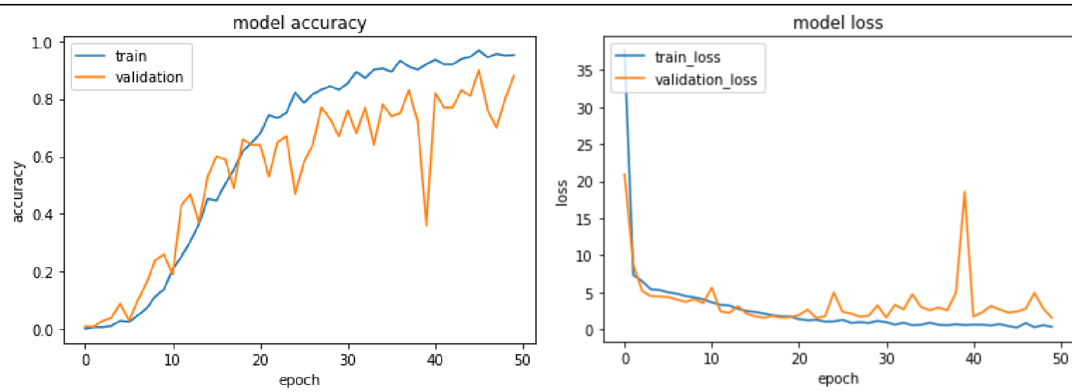


Fig. 9. AlexNet validation (a) accuracy and (b) loss on NITG database

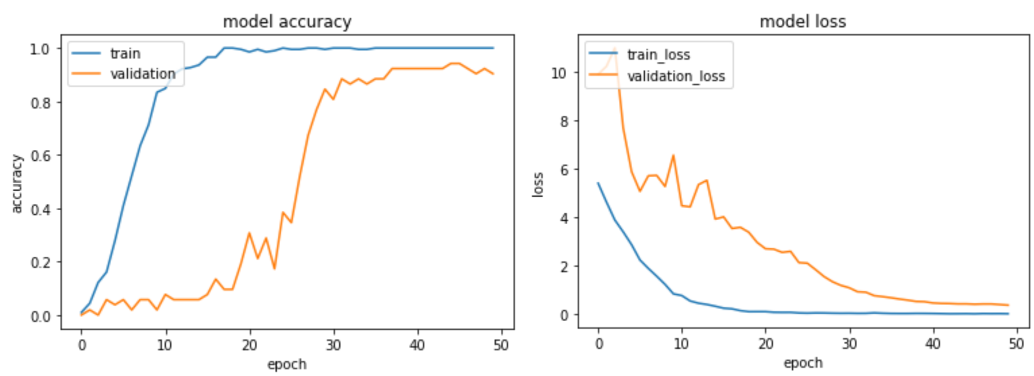


Fig. 10. AlexNet validation (a) accuracy and (b) loss on CMB database

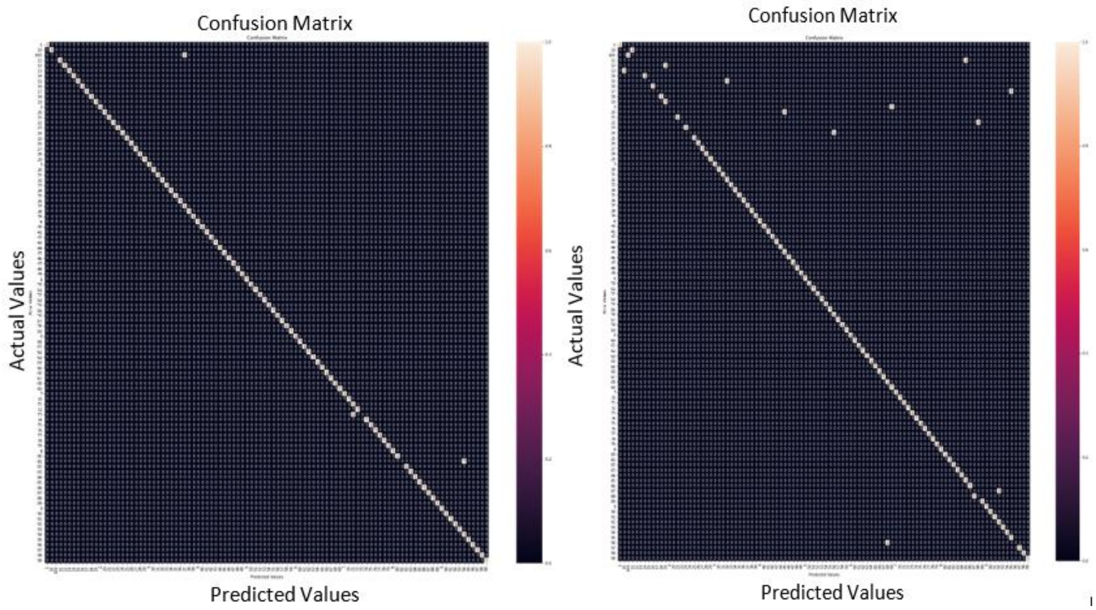


Fig. 11. Confusion matrix of AlexNet model on (a) NITG and (b) CMBD database

TABLE IV. SCORE LEVEL FUSION RESULT

Score Level Fusion	NITG		CMBD	
	`Rank 1	Rank 10	Rank 1	Rank 10
Max Fusion	99	100	99	100
Sum Fusion	74.5	99	50	90
Product Fusion	56	98	43	67

The confusion matrix for both the databases is presented in the Fig. 11. In which the actual class versus predicted class is plotted. It is observed that more subjects from CMBD database are falsely classified than the NITG database as model accuracy is more for this database.

To improve the accuracy further, the hybrid mode is built by combining the scores of DCT with machine learning and AlexNet model. The Score level fusion [34] of CDCT features and Machine learning classifier with class wise identification score of AlexNet model is done. The rank1 and rank 10 accuracy for both the databases is shown in Table IV. As it is class wise identification score, max fusion is giving good accuracy because there are very few cases where both the algorithms falsely predict the same class.

The identification accuracy obtained with the proposed method is compared with the literature in Table V, Improvement in the accuracy is observed with the use of score level fusion.

TABLE V. COMPARISON OF PROPOSED METHOD WITH LITERATURE

Paper	Methods	Age	Identification Accuracy
A.K. Jain [15]	CNN, COTS	0-12 months	≤ 4 weeks 38.44 % > 4 weeks 73.98 %
Proposed	DCT. GNB and CNN	0 – 5 years	99 %

IV. CONCLUSION AND FUTURE SCOPE

This paper proposed a hybrid method of children fingerprint identification which is based on transform domain DCT and convolution feature extraction for local and global features of fingerprint images. DCT's standard deviation features with machine learning classifier Gaussian Naïve base gives comparable accuracy as that of CNN model accuracy. We can deploy simple model based on DCT and GNB for children's fingerprint recognition, where we have fewer databases instead of the heavy CNN model. In this way, computational complexity and the need for higher version hardware is reduced. However, for higher accuracy over the period we require deep neural network models only. Here the score level combination of both algorithms is the most appropriate generalized solution for a robust model of children fingerprint identification, that is 1:N comparison is studied and implemented for children fingerprints (unimodal). The frequency domain features using DCT and CDCT, which gives compact representation of fingerprint texture image, is presented first time in this paper. The rank-1 identification accuracy achieved is 99 % using Max fusion which is higher than the literature.

The future work for this research is considering the feature level fusion. The accuracy of the children recognition can improve by using multimodal fusion with multiple modalities or multiple algorithms.

REFERENCES

[1] Deb, Debayan et al. "Finding Missing Children: Aging Deep Face Features." ArXiv abs/1911.07538 (2019).

[2] V. Kamble and M. Dale, "Face Recognition of Children Using AI Classification Approaches," 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), 2021, pp. 248-251, Doi: 10.1109/ESCI50559.2021.9396891.

[3] Debayan Deb, Neeta Nain, and Anil K. Jain. Longitudinal Study of Child Face Recognition. In 2018 International Conference on Biometrics (ICB), pages 225–232, Feb 2018.

[4] S. Bharadwaj, H. S. Bhatt, M. Vatsa, and R. Singh. Domain specific learning for newborn face recognition. IEEE Transactions on Information Forensics and Security, 11(7):1630–1641, 2016.

[5] R. P. Lemes, O. R. P. Bellon, L. Silva and A. K. Jain, "Biometric recognition of newborns: Identification using palmprints," 2011 International Joint Conference on Biometrics (IJCB), 2011, pp. 1-6, Doi:10.1109/IJCB.2011.6117475.

[6] E. Liu, "Infant Footprint Recognition," 2017 IEEE International Conference on Computer Vision (ICCV), 2017, pp. 1662-1669, Doi: 10.1109/ICCV.2017.183.

[7] S. Tiwari, S. Kumar, S. Kumar and G. R. Sinha, "Ear recognition for newborn," 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom), 2015, pp. 1989-1994.

[8] Tiwari, S., & Singh, S. K. (2012), 'Newborn Verification Using Headprint', Journal of Information Technology Research, 5(2), 15 -30

[9] https://onin.com/fp/fphistory.html, 'The History of Fingerprints'accessed on 29/09/2021.

[10] F. Galton, "Finger Prints of Young Children," British Association for the Advancement of Science, vol. 69, pp. 868–869, 1899.

[11] "Fingerprint Recognition for Children," Joint Research Center of the European Commission, Tech. Rep., 2013. [Online.] Available: https://ec.europa.eu/jrc/en/publication/eur-scientific-andtechnicalresearch-reports/fingerprint-recognition-children.

[12] V. Camacho et al., "Recognizing Infants and Toddlers over an On-Production Fingerprint Database," 2017 International Conference of the Biometrics Special Interest Group (BIOSIG), 2017, pp. 1-5, doi: 10.23919/BIOSIG.2017.8053518.

[13] J. Preciozzi et al., "Fingerprint Biometrics from Newborn to Adult: A Study From a National Identity Database System," in IEEE Transactions on Biometrics, Behavior, and Identity Science, vol. 2, no. 1, pp. 68-79, Jan. 2020, doi: 10.1109/TBIOM.2019.2962188.

[14] R. Haraksim, J. Galbally, and L. Beslay, "Fingerprint growth model for mitigating the ageing effect on childrens fingerprints matching," Pattern Recognition, vol. 88, pp. 614–628, 2019.

[15] Y. Koda, T. Higuchi, and A. K. Jain, "Advances in capturing child fingerprints: A high resolution CMOS image sensor with SLDR method," in International Conference of the Biometrics Special Interest Group (BIOSIG), 2016.

[16] Kalisky, T., Saggese, S., Zhao, Y. et al. Biometric recognition of newborns and young children for vaccinations and health care: a non-randomized prospective clinical trial. Sci Rep 12, 22520 (2022). https://doi.org/10.1038/s41598-022-25986-6.

[17] Engelsma JJ, Deb D, Jain AK, Sudhish PS, Bhatnager A: InfantPrints: Fingerprints for Reducing Infant Mortality. arXiv e-prints. 2019.

[18] P Macharia, P Muiruri, P Kumar, B Ngari, R Wario," The Feasibility of Using an Android-Based Infant Fingerprint Biometrics System for Treatment Follow-Up" 11th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2018) At: Portugal.

[19] J. J. Engelsma, D. Deb, K. Cao, A. Bhatnagar, P. S. Sudhish and A. K. Jain, "Infant-ID: Fingerprints for Global Good," in IEEE Transactions on Pattern Analysis and Machine Intelligence, doi: 10.1109/TPAMI.2021.3057634.

[20] A. K. Jain, K. Cao, and S. S. Arora, "Recognizing infants and toddlers using fingerprints: Increasing the vaccination coverage," IEEE International Joint Conference on Biometrics, Clearwater, FL, 2014, pp. 1-8.

[21] Jain Anil K, Arora Sunpreet S, Best-Rowden Lacey, Cao Kai, Sudhish Prem Sewak, Bhatnagar Anjoo, Biometrics for Child Vaccination and Welfare: Persistence of Fingerprint Recognition for Infants and Toddlers. arXiv preprint arXiv:1504.04651, 2015.

[22] A. K. Jain, S. S. Arora, L. Best-Rowden, K. Cao, P. S. Sudhish, A. Bhatnagar, and Y. Koda, "Giving infants identity: Fingerprint sensing and recognition," in ICTD, 2016.

[23] A.K. Jain, A.K. Aroda, S.S. Cao, L. Best-Rowden, and A. Bhatnager, "Fingerprint recognition of young children," in IEEE Transactions on Information Forensics and Security, vol. 12, no. 7, July 2017, pp. 1501-1514.

[24] A. R. Patil, A. D. Rahulkar and C. N. Modi, "Designing an Efficient Fingerprint Recognition System for Infants and Toddlers," 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2019, pp. 1-7, doi: 10.1109/ICCCNT45670.2019.8944342.

[25] Y. Moolla, A. De Kock, G. Mabuza-Hocquet, C. S. Ntshangase, N. Nelufule and P. Khanyile, "Biometric Recognition of Infants using Fingerprint, Iris, and Ear Biometrics," in IEEE Access, vol. 9, pp. 38269-38286, 2021, doi: 10.1109/ACCESS.2021.3062282.

[26] A. Jain, Fundamentals of Digital Image Processing, Englewood Cliffs, NJ: Prentice-Hall, 1989.

[27] A. Krizhevsky, I. Sutskever, and G. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks",Advances in Neural Information Processing Systems 25 , Curran Associates, Inc., (2012).

[28] Lin Hong, Yifei Wan and A. Jain, "Fingerprint image enhancement: algorithm and performance evaluation," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 8, pp. 777-789, Aug. 1998, doi: 10.1109/34.709565.

[29] Anil K. Jain, Salil Prabhakar, Lin Hong and Sharad Pankanti, "Filterbank based Fingerprint Matching", IEEE Transaction on Image Processing, Vol. 9, No. 5, May 2000.

[30] P. Basak, S. De, M. Agarwal, A. Malhotra, R. Singh, and M. Vatsa. Multimodal Biometric Recognition for Toddlers and Pre-School Children, In IEEE International Joint Conference On Biometrics, 2017.

[31] A K Samantaray, A D Rahulkar, P J Edavoor, "A Novel Design of Dyadic db3 Orthogonal Wavelet Filter Bank for Feature Extraction", Circuits, Systems, and Signal Processing, Springer, Vol 40, pp.5401-5420, April 2021.

[32] Chen, RC., Dewi, C., Huang, SW. et al. Selecting critical features for data classification based on machine learning methods. J Big Data 7, 52 (2020). https://doi.org/10.1186/s40537-020-00327-4.

[33] Introduction to Machine Learning Notes-https://www.cs.cmu.edu/~epxing/Class/10701-10s/ Lecture/lecture5.pdf.

[34] Kamel Aizi, Mohamed Ouslim,, Score level fusion in multi-biometric identification based on zones of interest, Journal of King Saud University - Computer and Information Sciences, Volume 34, Issue 1, 2022, Pages 1498-1509, ISSN 1319-1578, https://doi.org/10.1016/j.jksuci.2019.09.003.