K-Means Clustering with Deep Learning for Fingerprint Class Type Prediction

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Summary
In deep learning classification tasks, most models frequently assume that all labels are available for the training datasets. As such strategies to learn new concepts from unlabeled datasets are scarce. In fingerprint classification tasks, most of the fingerprint datasets are labelled using the subject/individual and fingerprint datasets labelled with finger type classes are scarce. In this paper, authors have developed approaches of classifying fingerprint images using the majorly known fingerprint classes. Our study provides a flexible method to learn new classes of fingerprints. Our classifier model combines both the clustering technique and use of deep learning to cluster and hence label the fingerprint images into appropriate classes. The K means clustering strategy explores the label uncertainty and high-density regions from unlabeled data to be clustered. Using similarity index, five clusters are created. Deep learning is then used to train a model using a publicly known fingerprint dataset with known finger class types. A prediction technique is then employed to predict the classes of the clusters from the trained model. Our proposed model is better and has less computational costs in learning new classes and hence significantly saving on labelling costs of fingerprint images.

Key words:
Clustering, Deep learning, Fingerprint classification, Transfer learning, Prediction

1. INTRODUCTION

Fingerprint play an important role in identification systems. Automatic fingerprint Identification systems (AFIS) have been used in identification of individuals and in verification of individuals. While identification requires one-to-many matching, verification is a process that requires a one-to-one matching. AFIS systems are used in many areas including border control points, Insurance schemes, accessing smartphones banking halls and even in hospitals for identification of patients. Fingerprints can also be applied in tracking immunization schedules for children attending immunization clinics to determine their promptness.

AFIS require high response times and for security purposes low false acceptance rates [1]. For effective response times and better search speeds, fingerprint classification modules have been incorporated into AFIS systems. It is well known, most of fingerprint image recognition tasks require Deep Learning (DL) techniques to classify and recognize fingerprints. However, its widely known that such task require vast amounts of labelled data. In some scenarios, there could be limited data that is labelled. Fingerprint datasets labelled with the widely known classes; Whorl, Left Loop, right Loop, arch and Tented arch are scarce. As such many fingerprint recognition tasks are classified using the subjects (individuals) as the classes. This implies that during data collections, several impressions of each fingerprint need to be collected for effective classification to be performed. Even with this approach, the datasets collected are still small for fingerprint classification tasks. Children fingerprint datasets are also considered very private and thus not easily available for research. Even so, they are not labelled into the five widely known classes. Yet, identification of children using fingerprints can be very useful in tracking immunization schedules for children hence reduction of mortality rates. Classifications tasks for such fingerprint datasets require labelled data. The use of multi-layered Convolutional neural network mainly referred to as deep learning is a major approach used to perform these classification tasks. Transfer learning-an approach of deep learning-is one major technique used in fingerprint classification tasks. Transfer learning enables one to reuse knowledge acquired from previously trained tasks into new tasks [2]. It's an effective method that works especially when the datasets are small in size. Transfer learning helps to improve the learning performance of a neural network by reduction of time used in learning from scratch. There are several deep learning architectures developed in recent times such as region-based CNN, faster region-based CNN [3], YOLO [4], AlexNet [5], ResNet [6], etc.

Unlike classification techniques which require labelled datasets, unsupervised learning techniques are used to cluster dataset without the need of labelled datasets. Most fingerprint datasets available publicly are not classified into the five major classes as described by [7]. Hence there is need of employing techniques that can be used to group fingerprints into widely known fingerprint classes. Unsupervised learning methods are used to group datasets that do not have labels. The two major unsupervised methods are clustering and association.

Manuscript received March 5, 2022
Manuscript revised March 20, 2022
https://doi.org/10.22937/IJCSNS.2022.22.3.5

Association technique [8] is a technique that tries to find associations between different subjects. The common problem used in association is the Market Basket analysis, which generally gets insights into what customers purchase

Another technique of unsupervised learning is the clustering technique. Clustering is used to segregate data into several clusters with similar characteristics. Examples of Clustering algorithms are Fuzzy K means, K-Means, Hierarchical, DBSCAN, etc. There are a large number of real-world applications for clustering. This includes; image segmentation techniques, clustering of consumer information, etc. K means clustering is the most commonly used techniques. It can be used for image analysis as well

In this paper, K means clustering is used to group images and then using transfer learning, we try to predict the classes (fingerprint types) of the clusters found. The paper tries to answer the question on whether we can automatically group images into meaningful clusters when labels are not available.

One major challenge of K means clustering is determining the value of K, which is the initial value of number of collections that groups the data according to different similarity patterns. The K value greatly affects the convergence results in clustering. [9]

Several researches have devised ways of determine the value of K. The methods include the elbow Method, Gap Statistic, Silhouette Coefficient, and Canopy [10]. World-wide known fingerprint classes are five, hence the k value determined for this research was five. Our research looks into predicting finger type classes, and hence clustering and deep learning were both employed. Clustering was a significant step to obtain the required clusters for prediction. Deep learning using transfer learning was performed using a beknown pretrained model, the ResNet50. Finally, the weights obtained were used to predict finger type classes of the cluster obtained from clustering and even new finger prints for evaluation. This is the gap that is of interest to our study. Our technique can be a step ahead to bring about flexibility in fingerprint classification experiments where finger classes are used as labels. We employed the use of clustering algorithms to capture the similarities between images. We developed a User-friendly GUI tool that will be useful to users who may want to know the finger type classes of some fingerprints

The major contributions of this research are as follows:

An image enhancement algorithm using a unified framework residual dense network to improve the quality of the children fingerprint images collected using a standard scanner.

Combination of clustering and deep learning techniques to predict finger print class types based on Henry Galton classification

Development of a user-friendly system for user interaction and prediction of finger type classes.

2. RELATED WORKS

2.1. Fingerprint Classification

Most Automated fingerprint Information systems require that a query fingerprint is compared with all other fingerprints stored in the database. It's imperative that these databases can grow into enormous sizes, hence requiring numerous fingerprint comparisons. Fingerprint classification is used in ideal situations as the first phase of fingerprint recognition systems. The classification ais aimed at providing an indexing technique to decrease the number of comparisons. It is an essential step because it assists to search for a query finger with only the same type of fingerprints thus saving searching time and total time of recognition. The implies that fingerprint classification step is an important step since it helps decrease the total execution time with after the performance of recognition systems [11].

With fingerprint classification steps, it's possible to significantly reduce the number of evaluations by investigating only the fingerprint belonging to the same class as the probe fingerprint hence improving the performance of AFIS

2.2. Types of fingerprint classes

Several studies have been done on fingerprint class types. In the 19th century, a study by Jan Evangelista Purkinje [12] classified fingerprint types into nine classes. Further to this, Francis Galton proposed three classifications of fingerprints [13]. This was later to be improved by Edward henry who proposed the famous five classes of fingerprint types [7]. Henry's classification of fingerprint types into five classes is frequently utilized in most studies.

2.3. Basics for fingerprint classification

Fingerprint have three types of points that are used to classify them [14]. These are the core, the

Fig. 1:Fingerprint Classes (a) arch, (b) tented Arch, (c) Left Loop, (d) Right Loop, (e) Whorl Adopted from [15]

delta and the loop. The core is the innermost point of the ridge patter, the delta is the triangular center point where ridges converge while loop is made up of many ridges forming a "U" pattern. These three features lead to the development of the various types of fingerprints.

The various classes include and their rate of occurrences are as below [15] : Arch has a frequency of 3.7%; Tented Arch is 2.9%; Left Loop at 33.8%; Right Loop at 31.7%) and Whorl is at 27.9%. The Fingerprints belonging to the two loop classes are the most common while the Tented Arch class are the least.

Several studies have shown fingerprint classification using pretrained models. Most of these have been done using datasets that have labels. For instance, [16], applied transfer learning using the Resnet50 model to perform fingerprint classification They achieved a classification accuracy of 95.7% on the PolyU fingerprint dataset provided by Hong Kong Polytechnic University. The dataset labels were identified according to the subjects from whom the images were collected. In [11], the author developed a lightweight Convolutional Neural Network (CNN) for classification using the NIST SD04 dataset and achieved a classification accuracy of 93%. The Dataset is classified according the five major classes. The study by [17] demonstrated the performance of three pretrained CNNs on two datasets. The datasets were already labelled with the finger print type classes

Unsupervised techniques have also been used for fingerprint recognition tasks; one major advantage of unsupervised techniques is that they can be used in datasets that have no labels. A major characteristics of fingerprint datasets is that most of them are private (due to ethical issues) and the most of the available public datasets are not classified according the five major fingerprint types. A study by [1] proposed a fingerprint classification method using Fuzzy C means and Naïve Bayes classifier to classify fingerprints into four classes. Their research revealed that there was no need of using massive amounts of training data in performing fingerprint classification. They obtained a classification accuracy of 91% over a database of 100 images. However, in this study the images were first hand classified into four NIST classes before application of the Naïve Bayes theorem. Data clustering has also been used in clustering fingerprints according to quality as per the study by [18]. The authors used three levels of classification and in each level the fingerprints were classified into two clusters

In [19] the authors developed a fingerprint classification model using the Sim- Net unsupervised neural network model. They used the directional flow and singular points as the input features into the model. The extraction process for the directional flow and singular points was performed by first filtering the raw fingerprint image. Singular points were then extracted from the fingerprint image. The number of singular points extracted can affect the number of classes.

3. METHODS AND MATERIALS

The section below illustrated our approach. The novelty of this work is in using two models-supervised and unsupervised learning models (clustering and deep learning models) for image classification. The method section of this paper is organized as follows: first we describe how the two techniques run in parallel. We begin by showing how clustering was used to group similar fingerprint images into clusters. Then using transfer learning, we train a known fingerprint dataset and obtain a model with good accuracy. We then use the trained model to predict the exact fingerprint classes for the clusters. In essence two experiments were performed. Clustering of images using K means clustering method, model training using transfer learning and then predicting the classes of the clusters using the trained model.

3.1. Datasets

Two datasets were employed in this study. The first dataset is the public image dataset NIST SD04. It consists of 4000 images of size 512 by 512 pixels. The images are grayscale and they have been labelled into five classes- Whorl, Tented Arch, Arch, Left Loop and right Loop. Each fingerprint image has an associated text file that has information about the gender, acquisition date and the class label. There are 400 images in each class and the files are in PNG format. The choice of NIST SD04 dataset is informed by the fact that the image quality of the images is acceptable and the fingerprints all have class labels. Its freely available and many existing researches use it.

One of the famous techniques used to increase images in a dataset and reduce overfitting is applying augmentation on the dataset. In this experiment, Data augmentation techniques were employed in order to enhance classification accuracy, prevent overfitting and improve the network robustness. The augmentation techniques included rotation range of 180 degrees, zoom range at 0.1, width and height shift ranges at 0.1 and random horizontal and vertical flips.

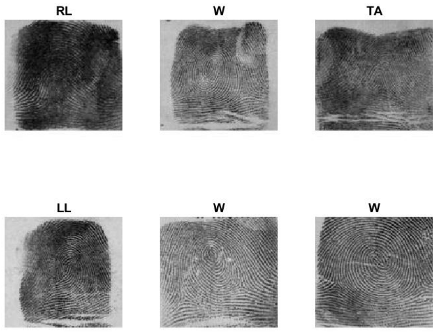

Fig 2: fingerprint classes from NIST Dataset

The second dataset is a private dataset collected from the field. The dataset contains 1400 images collected from children between ages two weeks and one year. Sample images collected are shown in fig.3. Being that the fingerprints were collected used the standard fingerprint sensor – mainly used for adults- the quality of the images was very low. Thus, the fingerprints were enhanced to increase their resolution and also make them easier for use in the experiments. Fingerprint image enhancement is a very effective tool for improving ridge clarity and unquestionably, a major factor for predetermination of success in matching accuracy. In enhancement, the major concern should be to improve a structure quality of fingerprints without interfering with the features. Enhancement also benefits in reducing spurious features and instead we get more accurate features

3.2. Fingerprint Image preprocessing

After data collection, we first enhanced the resolution of the fingerprint image using super-resolution using the Residual Dense Block (RDB) technique [20]. The RDB consists of three main components: the dense Connected layers, the local feature fusion and the local residual learning. Together they form a connecting memory mechanism where each layer is connected to all the previous layers in the network. Inspired DenseNet [21], this approach extracts and adaptively uses the extracted features from all previous layers efficiently. The two major advantages of the RDN are the use of both local features and global features. This leads to a dense feature vision with deep supervision. By use of DenseNet structure, the RDN transfers features between layers such that the output of each layer is given as the input to its succeeding layers. Consider the

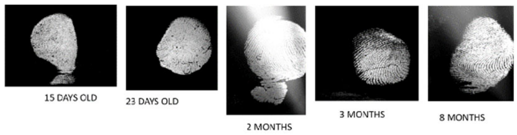

Fig. 3: Samples of collected fingerprint images

(y0, y1…yl-1) and yl to be inputs and output of the lth layer respectively such that:

$$yl=Hl\ ([y0, y1...yl-1]). \quad (1)$$

yl represents that concatenation of feature maps from preceding layers. The Hl function is the activation function that produces G feature maps. G is a hyper parameter that represents the growth rate such that the lth layer has G0+Gl-1 as input feature maps. The outputs of each layer have direct connections to all subsequent layers and this helps preserve useful hierarchical features.

We implemented the Residual Dense Network (RDN) in this research using the python Image Super Resolution (ISR) library. To further improve the image resolution, the resultant output image was further processed to refine the bifurcation using fingerprint enhancer whose technique is shown in [22]. An additional technique was added to invert the image such that the background was clear and image consisted of black lines (ridges)

3.3. Experiment one: Clustering of images using K means clustering

Generally, in Convolutional Neural networks (CNN), fingerprints features are not explicitly extracted. However, CNN can be applied for feature extraction alone and the features can be obtained for other purposes. In this experiment, ResNet 50 CNN architecture was used in feature extraction and then the features were used in the clustering module. K means clustering algorithm was applied for this task because of its simplicity. Selection of the exact number of clusters, k is generally unknown and can be a daunting task. Here, we choose k to be equal to the ground-truth clusters. This is mainly captured from the study of Henry Galton where fingerprints have been classified into five main classes, hence our k is five.

The image features in the private dataset were clustered using K means clustering technique in order to group them via similarity indexes. The similarity is measured using Euclidean distance. The K value chosen was five. This was informed by the world class accepted fingerprint types which are usually five (Arch, tented Arch, Whorl, Right Loop, Left loop).

Five clusters were obtained after the clustering process. One major disadvantage was that the clusters contained imbalanced data such that cluster A had 61 images Cluster B had 96 images, cluster C had 98 images Cluster D had 9 images and Cluster E had 88 images.

3.4. Experiment two: Deep learning model

In this experiment, fingerprint classification model was tra ting data split of 80% and 20%. The training data split is used for training purpose while the second test split was used for the testing purpose. The ResNet50 was trained on the training split. After training, the models are evaluated using testing split and a confusion matrix is obtained. The confusion matrix shows a visual presentation of the correct and wrong predictions. The following hyper-parameters were set for the training purpose.
Image size: 128 x 128
learning rate: 0.01
momentum: 0.1
output: 5 nodes

After training with 8 epochs, a classification accuracy of 86.5% was achieved. Training with higher number of epochs did not yield any difference in accuracy and hence eight epochs were selected as final. The training was done using MATLAB v20. The proposed model is shown in fig. 4.

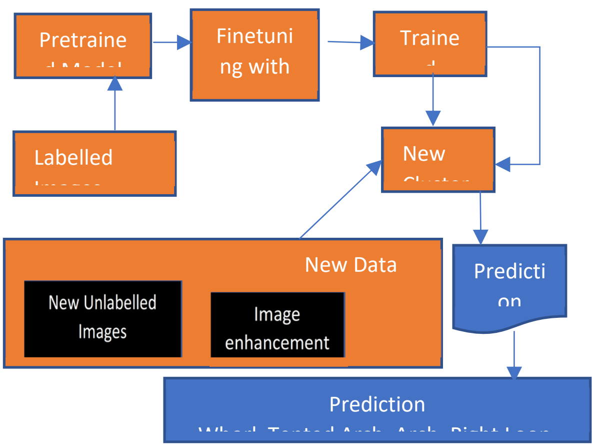

Fig. 4: Proposed model architecture

4. Experiment results

Training was performed using transfer learning on the public dataset NIST SD4. The Dataset has fingerprints grouped into five well known finger type classes.
An accuracy level of 86.5% was achieved as shown in fig. 5.

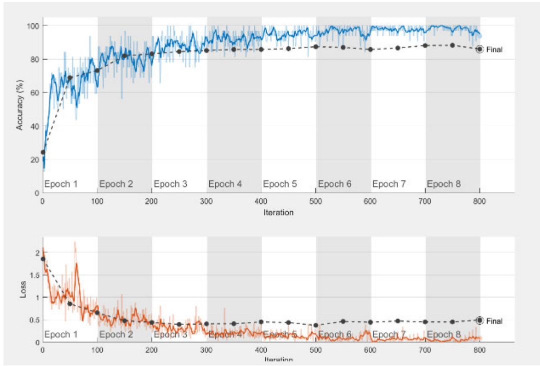

Fig. 5: Model Training and Validation Accuracies against number of epochs

4.1. Prediction module

The classes for the different clusters were obtained as shown in fig. 6 and table 1.
Given that most classes can easily overlap, the results indicate that some clusters contained all finger types. In this research we picked the highest finger type class as the probable finger type for that particular cluster.

Table 1: Predicted finger types for the different clusters

Cluster	Predicted Fingertypes
F	Right Loop
G	Right Loop
H	Right Loop
I	Left Loop
J	Left Loop

Fig. 6 indicates that the clusters could as well have contained more than one type of class. With the understanding that fingerprint types are not uniformly distributed in nature [23] thus the fingerprint types predicted show that most fingerprint are of type Right and Left loop. Cluster I, had a good number of Arch fingerprint class type too.

A user-friendly GUI based Prediction application module was developed from the implementation work. The prediction module was based on the trained model. The Application allows ease of prediction of a fingerprint class/type. The clusters obtained were fed into the prediction module to obtain the fingerprint classes for the clusters. Fig. 7 shows the prediction module developed.

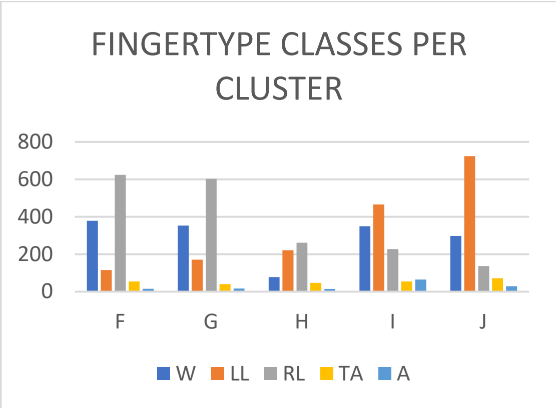

Fig. 6: Distribution of finger type per cluster

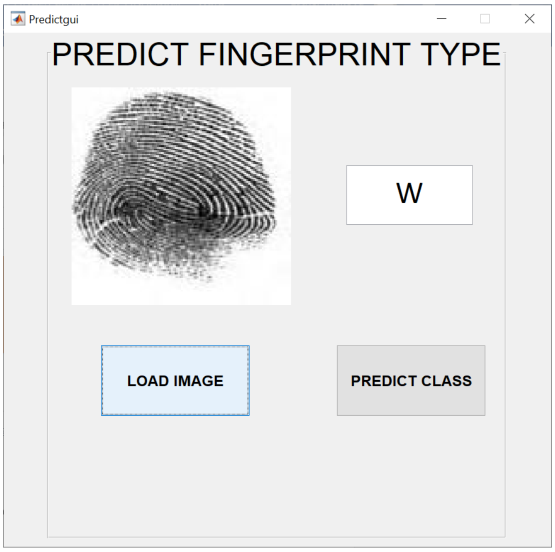

Fig. 7: Prediction module for fingerprint type

4.2. Evaluation of the Prediction Module

Evaluation of a developed tool is an important step in determining the effectiveness of the module. It helps to identify areas for improvement.

In this experiment, we evaluated our prediction module by using different dataset to predict their finger types. The dataset set used was the children multimodal dataset provided by [24]. The dataset consists of images for children aged between eighteen months and four years collected in two separate sessions. All the fingers were used in the data collection and five samples were collected for each sample. The fingerprints were pre-processed to obtained the same sizes as required by the model.

4.3. Comparisons with Previous studies

Fingerprint image datasets can be divided into human-interpretable fingerprint classes which follows the Henry-Galton–Henry structure or into machine-generated fingerprint classes [25]. Machine generated classes are partitioned with regard to similarity criteria of the features extracted from the fingerprint images. This is done in unsupervised manner such as use of clustering techniques. The study by [26] developed a fingerprint classes technique using the agglomerative hierarchical clustering technique. The images were classified based on the neighborhood of each image. They analyzed their performance using the False Acceptance Rate and classification accuracy. There accuracy reached 97%. The study by [27] explored the use of LSTM in fingerprint identification. Unlike CNN models, the inputs to the model are features extracted using the SURF techniques. Our research combines both use of unsupervised and supervised techniques to develop a model for predicting fingerprint classes. Unsupervised techniques are used to extract features and create clusters. Supervised techniques are used to train a deep learning model. The clusters are then fed into the trained model to predict the classes. This approach is useful in getting labelled fingerprint datasets which can be used in many future researches.

5. Conclusion and Future Work

In this study a prediction model for finger types is proposed. In this model, both clustering and deep learning on a known dataset are used. A model is finetuned using deep learning in order to classify fingerprints into known classes. A classification accuracy of 86.5% was obtained. The unsupervised technique of clustering was performed on a different dataset with no labels and five clusters are obtained. The clusters are then fed into the finetuned model in order to predict their possible finger type classes. The prediction module developed can be used with different settings to be able to naturally group the different fingerprints into the five major classes.

Future work may involve using alternative algorithms for clustering to obtain clusters that can be predicted by the developed model. Experiments with different datasets too can be explored

Acknowledgement

The authors of this paper would like to acknowledge the public hospital that allowed the researcher to collect data from the children visiting the clinics.
We also thank the parents and caregivers of children who gave consent on behalf of their children to help achieve the goal of this research.

References

[1] G Vitello et al, "A Novel Technique for Fingerprint Classification Based on Fuzzy C-Means and Naive Bayes Classifier," in Eighth International Conference on Complex, Intelligent and Software Intensive, 2014.

[2] L. Listyalina and I. Mustiadi, "Accurate and Low-cost Fingerprint Classification via Transfer Learning," in 5th International Conference on Science in Information Technology (ICSITech), Yogyakarta, Indonesia, 2019.

[3] Ren S, He K, Girshick R, Sun J, "Faster r-cnn: Towards real-time object detection with region proposal networks.," *Advances in neural information processing systems,* vol. 28, pp. 91-99, 2015.

[4] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR,* pp. 779-788, 2016.

[5] Krizhevsky, A.; Sutskever, I.; Hinton, G.E., "ImageNet classification with deep convolutional neural networks.," *Communications of the ACM,* vol. 60, no. 6, pp. 84-90, 2017.

[6] He, K.; Zhang, X.; Ren, S.; Sun, J., "Deep Residual Learning for Image Recognition.," in *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,*, Computer Vision and Pattern Recognition, Seattle, WA, USA, 21–23 June 2016; pp. 770–778., 2016.

[7] E. Henry, "Classification and Uses of Finger Prints," 1900. [Online]. Available: https://galton.org/fingerprints/books/henry/henry-1900-classification-1up.pdf. [Accessed 17th August 2021].

[8] H. Xu, X. Liang, W. Cui and W. Liu et al, "Research on an Improved Association Rule Mining Algorithm, 2019," *IEEE International Conference on Power Data Science (ICPDS),* pp. 37-42, 2019.

[9] HAN Ling-bo, WANG Qiang,JIANG Zheng-feng , "Improved k-means initial clustering center selection algorithm," *Computer Engineering and Applications,* vol. 46, no. 17, pp. 150-152, 2010.

[10] Yuan C, Yang H, "Research on K-Value Selection Method of K-Means Clustering Algorithm," *J : Multidisciplinary and Scientific journal,* vol. 2, no. 2, pp. 226-235, 2019.

[11] WEN JIAN, YUJIE ZHOU, AND HONGMING LIU, "Lightweight Convolutional Neural Network Based on Singularity ROI for Fingerprint Classification," *IEEE ACCESS,* vol. 8, no. 2020, pp. 54554-54563, 2020.

[12] Grzybowski A, Pietrzak K., "Jan Evangelista Purkynje (1787–1869): First to describe fingerprints," *Clinics in Dermatology,* vol. 33, no. 1, pp. 117-121, 2015.

[13] "Francis Galton: Fingerprinter," 1892. [Online]. Available: https://galton.org/books/finger-prints/index.htm. [Accessed 17 August 2021].

[14] Thai Hoang Le, Hoang Thien Van, "Fingerprint reference point detection for image retrieval based on symmetry and variation," *Pattern Recognition,* vol. 45, no. 9, pp. 3360-3372, 2012.

[15] Zabala-Blanco D, Mora M, Barrientos RJ, Hernández-García R, Naranjo-Torres J, "Fingerprint Classification through Standard and Weighted Extreme Learning Machines," *Applied Sciences,* vol. 10, 2020.

[16] Shervin Minaee, Elham Azimi, and Amirali Abdol rashidi., " Fingernet: Pushing the limits of fingerprint recognition using convolutional neural network.," *arXiv preprint arXiv:1907.12956, ,* 2019..

[17] Militello, C.; Rundo, L.; Vitabile, S.; Conti, V., "Fingerprint Classification Based on Deep Learning Approaches: Experimental Findings and Comparisons.," *Symmetry,* vol. 13, no. 5, p. 750, 2021.

[18] M.U. Munir, M.Y. Javed, S.A. Khan, "A hierarchical k-means clustering based fingerprint quality classification," *Neurocomputing,* vol. 85, pp. 62-67, 2012.

[19] Özbayoğlu Ahmet Murat, "Unsupervised Fingerprint Classification with Directional Flow Filtering," in *1st International Informatics and Software Engineering Conference (UBMYK),*, Ankara Turkey, 2019.

[20] Zhang Y, Tian Y, Kong Y, Zhong B, Fu Y, "Residual dense network for image super-resolution.," in *Proceedings of the IEEE conference on computer vision and pattern recognition.*, 2018.

[21] G. Huang, Z. Liu, and K. Q. Weinberger., "Densely connected convolutional networks," in *In IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

[22] Lin Hong, Yifei Wan, and Anil Jain, "Fingerprint Image Enhancement: Algorithm and Performance Evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* pp. vol. 20, no. 8, pp. 777-789, 1998.

[23] S. JM., "Fingerprint classification using convolutional neural networks and ridge orientation images," *IEEE Symposium Series on Computational Intelligence (SSCI),* pp. 1-8, 2017.

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

[25] X. Jiang, "Fingerprint Classification," in *In: Li S.Z., Jain A. (eds) Encyclopedia of Biometrics*, Boston, Springer, 2009.

[26] Bhattacharyya, M. H. Bhuyan and D. K., "An Effective Fingerprint Classification and Search Method," *International Journal of Computer Science and Network Security,* vol. 9, no. 11, pp. 39-68, 2012.

[27] Nithya B, Sripriya P. , "Fingerprint Identification by Training a LSTM Network with Fingerprint Segments as Sequence Inputs," in *2021 6th International Conference on Communication and Electronics Systems (ICCES)*, Coimbatre, India, 2021.

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