ISSN 1596-7026
2018 | Vol. 23 (1) | pp. 84 - 90
Science Focus
An International Journal of Biological and Physical Sciences – www.sciencefocuslautech.org
Faculty of Pure and Applied Sciences, LAUTECH, Ogbomoso. Printed in Nigeria

https://doi.org/10.36293/sfj.2019.0029

FINGERPRINT PHENOTYPING FOR ETHNICITY CLASSIFICATION: A GENERATIVE DEEP LEARNING PERSPECTIVE

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Abstract

In recent years, deep learning techniques have already been impacting wide range of information processing, pattern recognition, image processing and computer vision related works within the traditional and widened scopes. Hence, this research explored a generative deep architecture approach to better engage soft and hard biometric features for identification and classification of individual persons into their respective ethnic divides.

***Keywords**: Deep learning, Fingerprint classification, Ethnicity identification, Recognition accuracy*

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Introduction

Deep Learning is tied in with learning different degrees of portrayal and reflection that help to understand information, for example, pictures, sound and content. It alludes to a class of AI procedures, where numerous layers of data handling stages in progressive structures are explored for example grouping and for highlight or portrayal learning .

Deep learning has equally described by as a powerful form of machine learning that enables computers to solve perceptual problems such as image and speech recognition. Deep learning is invaluable in the area of big data as it extracts high-level information from very large volumes of data. Deep learning is about accurately assigning credit across many such stages . In the works of , Deep Learning was recognized as increasing increasingly more fame because of its accomplishment in different applications like Natural Language Processing (NLP), Image recognition and other Machine Learning paradigms.

I broadly classified Deep Learning architectures into three main classes i.e. Generative Deep Architectures, Discriminative Deep Architectures and Hybrid Deep Architectures. Generative Deep Architectures are planned to portray the high-order correlation properties of the watched or obvious information for pattern analysis or amalgamation purposes and describe the joint measurable circulations of the unmistakable information and their related classes

Discriminative Deep Architectures be that as it may, are expected to straightforwardly give discriminative capacity to pattern classification frequently by describing the back dispersions of classes molded on the visible data. Hybrid Deep Architecture is where the objective is segregation however helped with the results of generative architectures through better streamlining and regularization. Then again, discriminative criteria are utilized to become familiar with the parameters in any of the deep generative models in Generative Deep Architectures.

With current trends of event, especially where many societies become more and more multicultural, the issue of ethnicity which is the subjective attachment people have to ethnic communities cannot be underplayed. Infact, it is often used to predict educational and professional outcomes, networking opportunities, economic status, living conditions, partner selection and marital success. Ethnic identification is of high importance as it has the capability to control, limit and enhnace opportunities for wellbeing in our society .

However, if ethnic classification does not go beyond appearance based assessment, the tendency for misclassification is very high , the possibility for manipulation and spoofing is more evident which thereby poses serious adverse implication on the system's integrity and security . Hence, this work phenotyped fingerprint biometric technique for ethnic classification from a generative deep learning perspective.

Past Related Works

In man's daily activities, there is usually the need to identify who you are in order to get a certain kind of service; hence personal identification has a great deal of influence on what becomes of you and your level of success in life. In essence, the relevance of biometrics in modern society has been reinforced by the need for large scale identity management systems whose functionality relies on the accurate determination of an individual's identity in the context of several different applications . Invariably, biometrics is increasingly solid and progressively fit for recognizing a particular individual and an impostor than any system dependent on distinguishing proof report or secret phrase. This section x-rayed different biometric approaches used by past authors in identifying individual's personality with particular focus on unsupervised deep learning approach.

Fingerprint classification according to is said to be a successful procedure for diminishing competitor's quantities of fingerprints in the phase of coordinating in automatic fingerprint identification system (AFIS). In the paper, the orientation field was picked as the input feature and another method (stacked sparse auto encoders) in light of depth neural network was received for fingerprint classification. For the four-class issue, a classification of 93.1 percent was accomplished utilizing the depth network structure which has three shrouded layers (with 1.8% dismissal) in the NIST-DB4 database. By just altering the probability threshold, classification accuracy of 96.1% (setting threshold is 0.85), 97.2% (setting threshold is 0.90) and 98.0% (setting threshold is 0.95) was gotten. Utilizing the fuzzy method, higher accuracy than different methods was acquired.

Lagree & Bowyer (2011) examined the possibility of predicting ethnicity based on iris texture in a bid to narrow down the search of an enrollment database for a match to probe sample. An iris image dataset of 120 persons with 10-fold disjoint cross validation was used. About 91% correctness of Asian/Caucasian ethnicity was obtained. Range information of human faces for ethnicity identification using a support vector machine was expored by. A reconciliation plan is additionally proposed for ethnicity and gender identifications by joining the enlisted range and force pictures. The analyses were led on a database containing 1240 facial scans of376 subjects. It was shown that the range methodology gives aggressive discriminative power on ethnicity and gender identifications to the force methodology. For both gender and ethnicity identifications, the proposed joining plan beat every individual methodology.

Latinwo et al. (2018) classified iris images from Nigeria, China and Hong Kong origin using Self-Organizing Feature Maps (SOFM) blended with Principal Component Analysis (PCA) based Feature extraction. Left and right irises of 240 subjects constituting 480 images were acquired online from CUIRIS (Nigeria), CASIA (China) and CUHK (Hong Kong) datasets, and normalized to a uniform size of 250 by 250 pixels. Three hundred and thirty six (336) images were used for training while the remaining 144 were used for testing. Correct Classification Rate (CCR) of 93.75% was obtained in the research.

The performance of selected feature extraction techniques for ethnicity classification was evaluated by . For the work, fingerprint images of one thousand and fifty-four (1054) persons of three different ethnic groups (Yoruba, Igbo and Middle-Belt) in Nigeria were captured. Kernel Principal Component Analysis (K-PCA) and Kernel Linear Discriminant Analysis (KLDA) were used independently for feature extraction while Convolutional Neural Network (CNN) was used for supervised learning of the features and classification. The results showed that out of sixty (60) individual fingerprints tested, eight (8) were classified as Yoruba, forty-eight (48) as Igbo and four (4) as Hausa. The Recognition Accuracy for K-PCA was 93.97% and KLDA was 97.26%.

A hybrid CNN-GWO approach for the recognition of human actions from the unconstrained videos was proposed by . In the work, the weight initializations for the proposed Deep Convolutional Neural Network (CNN) classifiers exceptionally rely upon the created arrangements of GWO (Gray Wolf Optimization) algorithm, which thusly limits the 'grouping' blunders. The activity bank and nearby spatio-transient highlights are produced for a video and bolstered into the 'CNN' classifiers. The 'CNN' classifiers are prepared by an inclination plunge algorithm to identify a 'nearby least' during the wellness calculation of GWO 'search agents'. The GWO algorithms 'global search' capacity just as the slope drop algorithms 'neighborhood search' abilities are oppressed for the distinguishing proof of an answer which is closer to the global ideal. At last, the order execution can be additionally upgraded by intertwining the classifiers confirmations created by the GWO algorithm. The proposed characterization structures productivity for the acknowledgment of human activities is assessed with the assistance of four reachable activity acknowledgment datasets in particular HMDB51, UCF50, Olympic Sports and Virat Release 2.0. The exploratory approval of our proposed methodology shows better feasible outcomes on the acknowledgment of human activities with 99.9% acknowledgment precision.

Raza & Singh (2018) x-rayed the performance of unsupervised deep learning on medical image analysis. The work revealed that unlike supervised learning which is biased towards how it is being supervised and manual efforts to create class label for the algorithm, unsupervised learning derive insights directly from the data itself, group the data and help to make data driven decisions without any external bias. The review presented various unsupervised

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models applied to medical image analysis, including autoencoders and its several variants, Restricted Boltzmann machines, Deep belief networks, Deep Boltzmann machine and Generative adversarial network.

An unsupervised Deep Embedded Clustering (DEC) analysis was proposed by , this is a method that simultaneously learns feature representations and cluster assignments using deep neural networks. DEC learns a mapping from the data space to a lower-dimensional feature space in which it iteratively optimizes a clustering objective. The experimental evaluations on image and text corpora showed significant improvement over state-of-the-art methods.

Zong et al. (2018) emphasized the significance of unsupervised anomaly detection on multi-dimensional information in both crucial AI research and mechanical applications, for which thickness estimation lies at the center. The creators' research displayed a Deep Autoencoding Gaussian Mixture Model (DAGMM) for solo peculiarity identification. Their model used a profound autoencoder to create a low-dimensional portrayal and recreation blunder for each info information point, which is additionally bolstered into a Gaussian Mixture Model (GMM). DAGMM mutually advanced the parameters of the profound auto encoder and the blend model at the same time in a start to finish design, utilizing a different estimation system to encourage the parameter learning of the blend model. The joint improvement, which very much adjusted auto encoding remaking, thickness estimation of dormant portrayal, and regularization, helped the auto encoder escape from less alluring neighborhood optima and further diminished recreation mistakes, maintaining a strategic distance from the need of pre-preparing. Exploratory outcomes on a few open benchmark datasets demonstrated that DAGMM altogether outflanked best in class oddity identification systems, and accomplished up to 14% improvement dependent on the standard F1 score.99. Review of past related works revealed that deep learning approach to identification process is the way to go as it produces ground breaking results. However, no evident work has been done approaching ethnicity identification from deep generative point of view which this research addresses.

Method

In order to achieve the set objectives of identifying ethnicity of individuals using their fingerprint images and from Generative Deep learning perspective, the ten finger images of three thousand and five hundred (3500) subjects of three different ethnic groups (Yoruba, Urhobo and Tiv) in Nigeria were in essence, a total of 35,000 fingerprint images were captured directly from different persons and varying ethnic groups. The implementation of ethnicity identification framework as shown in Figure 1 followed series of operations to achieve the set objectives. Four different threshold values (0.15, 0.35, 0.45 and 0.75) for both left and right fingers were used to get varying outputs of which time taken for each threshold value were captured. Deep Belief Network was used as the generative deep learning algorithm for classification of fingerprint images into their respective ethnic groups.

The principle of greedy layer-wise unsupervised training was applied to DBNs with RBMs as the building blocks for each layer. The process is as follows:

1. Train the first layer as an RBM that models the raw input $x = h^{(0)}$ as its visible layer.

2. Use that first layer to obtain a representation of the input that will be used as data for the second layer. Two common solutions exist. This representation can be chosen as being the mean activations $p(h^{(1)} = 1|h^{(0)}|)$ or samples of $p(h^{(1)}|h^{(0)})$.
3. Train the second layer as an RBM, taking the transformed data (samples or mean activations) as training examples (for the visible layer of that RBM).
4. Iterate (2 and 3) for the desired number of layers, each time propagating upward either samples or mean values.
5. Fine-tune all the parameters of this deep architecture with respect to a proxy for the DBN log-likelihood, or with respect to a supervised training criterion (after adding extra learning machinery to convert the learned representation into supervised predictions).

Results

The result gives a description of the efficiency rate of using unsupervised deep learning algorithm for the purpose of ethnicity identification. The performance of the system was evaluated using metrics such as False Acceptance Rate, False Rejection Rate, Genuine Acceptance Rate, Accuracy and Recognition Time. The results are as shown for the three ethnic groups in Table 1.

A total of 3600 fingerprint images of Yoruba ethnic group were used to test the system with instances of 1800 inter marriage of Yoruba with other ethnic groups Tiv had 3400 fingerprint images with 1700 instances of inter marriage with other ethnic groups while 3000 fingerprint images of Urhobo with 1500 cases of inter marriage with other ethnic groups were used as well. Yoruba ethnic group had recognition accuracy is 97.89% while Tiv achieved recognition accuracy of 94.25% and Urhobo had recognition accuracy of 95.52%.

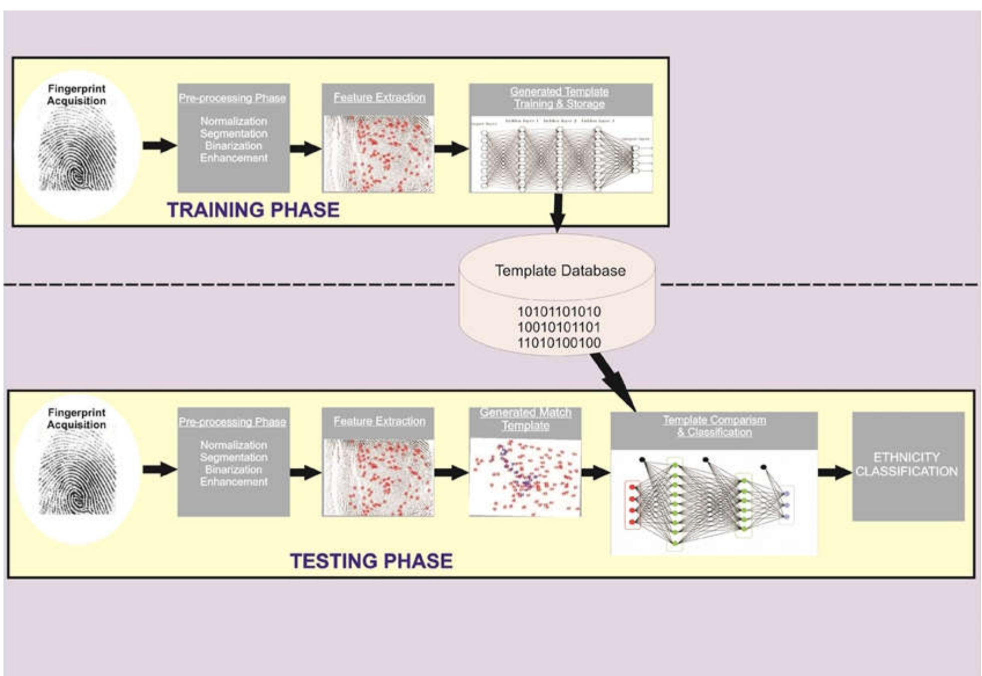

Figure 1 : Generative Framework for Ethnicity Identification

Table 1: The efficiency rate of using unsupervised deep learning algorithm for the purpose of ethnicity identification

Ethnic group	TP	FN	FP(In)	TN(In)	FRR (%)	FAR (%)	GAR (%)	ACC(%)	TIME(s)	Threshold
	3564	36	120	1680	1	6.67	99	97.11	1115.76	0.15
	3562	38	110	1690	1.06	6.11	98.94	97.26	1088.5	0.35
	3555	45	100	1700	1.25	5.56	98.75	97.31	1092.66	0.45
	3520	80	35	1765	2.22	1.94	97.78	97.87	1187.22	0.75
Tiv	3310	90	278	1422	2.65	16.35	97.35	92.78	1149.44	0.15
	3299	101	213	1487	2.97	12.53	97.03	93.84	1242.42	0.35
	3267	133	169	1531	3.91	9.94	96.09	94.08	1226.43	0.45
	3201	199	95	1605	5.85	5.59	94.15	94.24	1237.5	0.75
Urhobo	2929	71	299	1201	2.37	19.93	97.63	91.78	955.161	0.15
	2905	95	233	1267	3.17	15.53	96.83	92.71	1032.43	0.35
	2898	102	142	1358	3.4	9.47	96.6	94.58	1019.14	0.45
	2859	141	66	1434	4.7	4.4	95.3	95.4	1028.34	0.75

Conclusion

This research developed model that can match and determine ethnicity of certain individuals in Nigeria using fingerprint and deep learning approach; generative deep learning algorithm was use for this purpose. The performances of all the approaches were satisfactory with respect to their varying turnaround time and recognition accuracy.

The research substantiated that individual person's ethnicity can be identified through his/her fingerprint; verifying this is better done using deep learning algorithms due to their great capability for hierarchical feature extraction and data distribution approximation in high dimensional spaces.

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