Unique Fingerprint Liveness Recognition Utilizing Convolutional Neural Systems

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Abstract : With the developing utilization of biometric confirmation frameworks in the current years, parody finger print recognition has turned out to be progressively essential. In this paper, we utilize convolutional neural systems (CNNs) for fingerprint liveness discovery. Our framework is assessed on the informational indexes utilized as a part of the liveness location rivalry of the years 2009, 2011, and 2013, which contains very nearly 50000 genuine and phony fingerprints pictures. We think about five distinct models: three CNNs pretrained on regular pictures and fine-tuned with the fingerprint pictures, CNN with arbitrary weights, and an established neighborhood parallel example approach. We demonstrate that pretrained CNNs can yield the condition of-theart comes about with no requirement for design or hyperparameter determination. Informational index expansion is utilized to expand the classifiers execution, for profound models as well as for shallow ones. We likewise report great exactness on little preparing sets (400 examples) utilizing these huge pretrained systems. Our best model accomplishes a general rate of 98.1% of accurately classified tests—a relative change of 13.7% in test error when contrasted and the best already distributed outcomes.

IndexTerms **-Fingerprint acknowledgment, machine learning, regulated learning, neural systems.**

I. INTRODUCTION

THE BASIC point of biometrics is to naturally segregate subjects in a solid way for an objective application in light of at least one signs got from physical or behavioral characteristics, for example, fingerprint, confront, iris, voice, palm, or transcribed mark. Biometric innovation shows a few points of interest over traditional security strategies in light of either some data (PIN, Password, and so on.) or physical gadgets (scratch, card, and so on.) [2]. In any case, giving to the sensor a phony physical biometric can be a simple method to overwhelm the frameworks security. Fingerprints, specifically, can be effectively mock

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From normal materials, for example, gelatin, silicone, and wood stick [2]. In this way, a safe fingerprint framework should accurately recognize a farce from a true finger (Figure 1). Diverse fingerprint liveness identification calculations have been proposed [3]– [5], and they can be comprehensively partitioned into two methodologies: equipment and programming. In the equipment approach, a specific gadget is added to the sensor with a specific end goal to distinguish specific propertiesof a living attribute, for example, circulatory strain [6], skin distortion[7],or odor[8].In the product approach,which is utilized as a part of this investigation, counterfeit qualities are distinguished once the example has been obtained with a standard sensor. The highlights used to recognize genuine and counterfeit fingers are removed from the picture of the fingerprint. There are methods, for example, those in [2] and [9], in which the highlights utilized as a part of the classifier depend on specific fingerprint estimations, for example, edge quality, congruity, and lucidity. Interestingly, a few works utilize general element extractors, for example, Weber Local Descriptor (WLD) [10], which is a surface descriptor made out of differential excitation and introduction parts.

Another neighborhood descriptor that utilizations nearby plentifulness differentiate (spatial area) and stage (recurrence space) to shape a bi-dimensional complexity stage histogram was proposed in [11]. In [12] two general element extractors are analyzed: Convolutional Neural Networks (CNN) with irregular (i.e., not educated) weights (additionally investigated in [13]), and Local Binary Patterns (LBP), whose multi-scale variation revealed in [14] accomplishes great outcomes in fingerprint liveness recognition benchmarks.

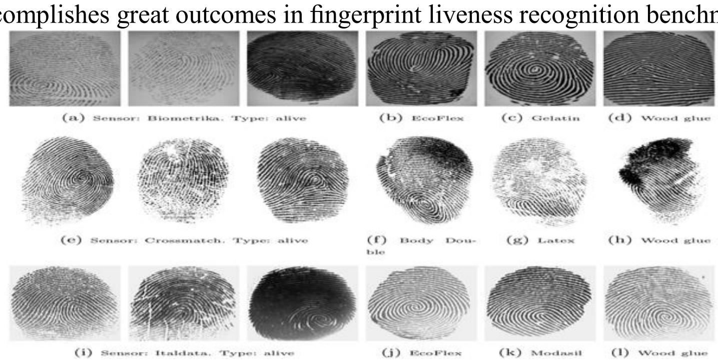

Fig. 1. Regular cases of genuine and phony fingerprint pictures that can be acquired from database utilized as a part of the tests.

As opposed to more advanced procedures that utilization surface descriptors as highlights vectors, for example, Local Phase Quantization (LPQ) [15], LBP with wavelets [16], and BSIF [17], their LBP usage utilizes the first and uniform LBP coding plans. In addition, an assortment of discretionary preprocessing strategies, for example, differentiate standardization, recurrence filtering, and locale of intrigue (ROI) extraction were endeavored without progress.

Expanded datasets [18], [19] are effectively used to build the classifiers power against little varieties by making extra examples from picture interpretations and level reflections. In this investigation we broaden the work displayed in [12] by utilizing a comparable model from the notable AlexNet [19],[1] pre-prepared on the ILSVRC-2012 dataset [20], which contains more than 1.2 million pictures and 1000 classes, and afterward fine-tuned on fingerprint pictures. We demonstrate that despite the fact that the pre-prepared model was intended to distinguish questions in common pictures, fine-tuning it to the undertaking of fingerprint liveness recognition yields preferred outcomes over if prepared the model utilizing arbitrarily introduced weights.

Besides, we prepare our framework utilizing a bigger pre-prepared model [21], VGG, the second place in the ILSVRC-2014 [20], to build the exactness of the classifier by another 2% in outright esteems. Therefore, the commitments of this examination are three-crease:

- Deep systems planned and prepared for the assignment of protest acknowledgment can be utilized to accomplish best in class exactness in fingerprint liveness location. No specific handengineered strategy for the errand of fingerprint liveness discovery was utilized. In this way, we give another achievement instance of exchange learning for profound learning procedures.
- Pre-prepared Deep systems require less named information to accomplish great precision in another assignment.
- Dataset enlargement builds precision for profound structures as well as for shallow systems, for example, LBP.

II. METHODOLOGY

Exchange Learning is an examination problemin machine discovering that spotlights on putting away information picked up while fathoming one issue and applying it to an alternate yet related issue. In this investigation, we demonstrated that it is conceivable to accomplish stateof-the-workmanship fingerprint liveness discovery by utilizing models that were initially composed and prepared to distinguish protests in characteristic pictures, (for example, creatures, auto, individuals). A similar thought is investigated in [22], for which the creators accomplished cutting edge execution in CIFAR-10, Flicker Style Wikipaintings benchmarks utilizing a pre-prepared convolutional arrange. One critical contrast from their investigations to our own is that all the datasets they utilized contain comparable pictures to the ImageNET dataset .

A. Models

Table I portrays the models in this examination. Every one of them utilize dataset expansion. Furthermore, we demonstrate the design of the models in Figure 3. For CNN-VGG and CNN-Alexnet, the engineering is the same as portrayed in [19] and [20], respectively,exceptthat we replacedthe last 1000-unitsoftmax layer by a 2-unit softmax layer (appeared in red in the figure), so the system can yield the 2 classes (if the picture is genuine or counterfeit) rather than the first 1000 classes that the systems were intended for. For the CNN-Random the design is distinctive for each dataset and it was picked through a broad network seek as portrayed in [12].

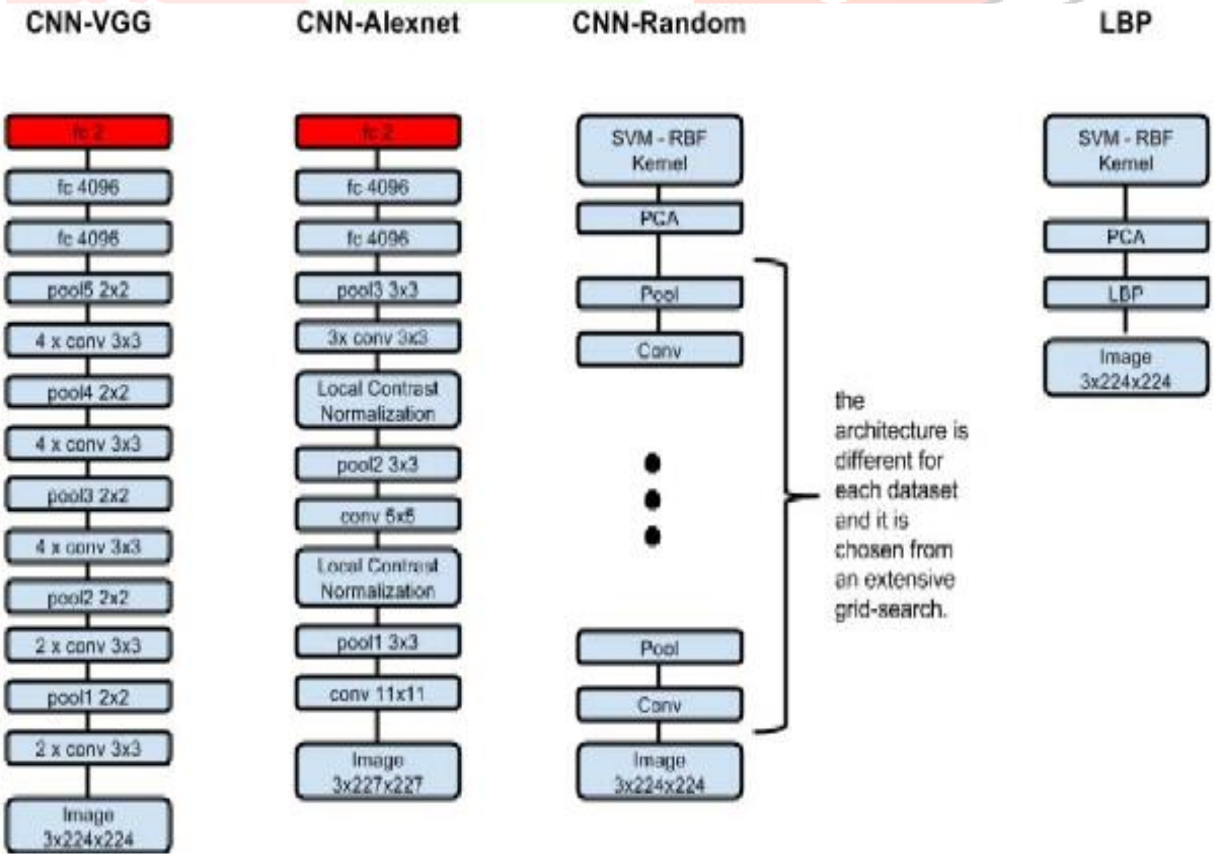

Fig. 2. Representation of the models utilized as a part of this investigation. The containers in red are the main layers that are unique in relation to the first VGG-19 and Alexnet models.

B. Convolutional Networks

Convolutional Networks [23] have shown state-ofthe-workmanship execution in an assortment of picture acknowledgment benchmarks, for example, MNIST [24], CIFAR-10 [24], CIFAR-100 [24], SVHN [24], and ImageNet [25]. An established convolutional organize is made out of exchanging layers of convolution and neighborhood pooling (i.e., subsampling). The point of a convolutional layer is to remove designs found inside nearby locales of the inputted pictures that are basic all through the dataset by convolving a format over the inputted picture pixels and yielding this as an element delineate, for each filter in the layer. A non-straight capacity f (c) is then connected elementwise to each component outline : a = f(c). A scope of capacities can be utilized for f (c), with max(0;c) a typical decision. The subsequent actuations f(c) are then passed to the pooling layer. This totals the data inside an arrangement of little nearby areas, R, delivering a pooled highlight outline (regularly of littler size) as the yield. Indicating the total capacity as pool(), for each element outline we have: sj = pool(f(ci))∀i ∈ Rj, whereRj is the pooling area j in include delineate and I is the record of every component inside it. Among the different sorts of pooling, max-pooling is ordinarily utilized, which chooses the greatest estimation of the locale Rj.

The inspiration driving pooling is that the initiations in the pooled delineate are less delicate to the exact areas of structures inside the picture than the first element outline. In a multi-layer demonstrate, the convolutional layers, which take the pooled maps as information, would thus be able to separate highlights that are progressively invariant to neighborhood changes of the info picture [26], [27]. This is imperative for classification undertakings, since these changes muddle the question personality. Accomplishing invariance to changes in position or lighting conditions, heartiness to mess, and minimization of portrayal, are altogether shared objectives of pooling.

The first one, CNN-Random, utilizes just arbitrary filter weights draw from a Gaussian appropriation. In spite of the fact that the filter weights can be scholarly, filters with arbitrary weights can perform well and they have the favorable position that they don't should be educated [28]–[30]. The design of the model is the same as that utilized as a part of [12]. It utilizes a convolutional connect with arbitrary weights as the component extractor, the measurements are additionally decreased utilizing PCA and a SVM classifier with RBF portions utilized as the classifier. A broad scan for hyper-parameter fine-tune was performed consequently on in excess of 2000 blends of hyper-parameters, recorded in table II. The best hyper-parameters were picked per sensor and per dataset (ex. Biometrika 2009, Bimetrika 2011, and so forth) through a 5 × 2 cross approval technique [31] which utilized the preparation dataset of every sensor in each LivDet dataset (2009, 2011, 2013).

The second model, CNN-Alexnet, is fundamentally the same as AlexNet [19], pre-prepared on the ILSVRC-2012 dataset.
This model won both classification and localization tasks in the ILSVRC-2012 rivalry. Their prepared model has been utilized to enhance exactness in an assortment of different benchmarks, for example, CIFAR-10, CIFAR-100. The pre-prepared system gives a decent beginning stage to taking in the system weights for different undertakings, for example, fingerprint liveness identification.

The third model, CNN-VGG, is fundamentally the same as the one utilized as a part of [21], a 19 layer CNN which accomplished the second place in the recognition errand of the ImageNet 2014 test. For CNN-ALEXNET and CNN-VGG models, the last 1000-unit delicate max layer (initially intended to foresee 1000 classes) was supplanted by a 2-unit softmax layer, which allocates a score for genuine and counterfeit classes. The pre-trainedmodel was additionally prepared with the fingerprint datasets. The calculation used to prepare CNN-Alexnet and CNN-VGG is the Stochastic Gradient Descent (SGD) with a minibatch of size 5, utilizing force [32], [33] 0.9 and a fixed learning rate of 10−6.

The forth model, CNN-Lenet (Fig 3) a spearheading 7-level convolutional organize by LeCun et al in 1998, that arranges digits, was connected by a few banks to perceive written by hand numbers on (checks) digitized in 32x32 pixel pictures. The capacity to process higher determination pictures requires bigger and more convolutional layers, so this procedure is compelled by the accessibility of registering assets.

TABLE 1 : Model Description

Model Name	Pipeline	Description
CNN-VGG	16 Convolutional Layers + 3 Fully Connected Layer	Pre-trained model from [20] and finetuned using liveness detection Datasets.
CNN-Alexnet	8 Convolutional Layers + 3 Fully Connected Layers	Pre-trained model from [18] and finetuned using liveness detection datasets
CNN-Random	CNN-Random+ PCA + SVM	Features are extracted using Convolutional Networks. The feature vector is reduced using PCA and then fed into a SVM classifier using RBF kernel.
CNN-Lenet	2 Convolutional Layers + 2 Fully Connected Layer + 2 Pooling Layers+ 1 Softmax Layer	The capacity to process higher determination pictures requires bigger and more convolutional layers, so this procedure is obliged by the accessibility of registering assets.
LBP	LBP + PCA + SVM	Features are extracted using LBP. The feature vector is reduced using PCA and then fed into a SVM classifier with (Gaussian) RBF kernel.

C. Local Binary Patterns

Neighborhood Binary Patterns (LBP) are a nearby surface descriptor that have performed well in different PC vision applications, including surface classification and division, picture recovery, surface review, and face location [34]. It is a generally utilized technique for fingerprint liveness recognition [14] and it is utilized as a part of this work as a standard strategy.

In its unique form, the LBP administrator relegates a mark to each pixel of a picture by thresholding every one of the 8 neighbors of the 3×3-neighborhood with the middle pixel esteem and considering the outcome as a one of a kind 8-bit code speaking to the 256 conceivable neighborhood mixes. As the examination with the area is performed with the focal pixel, the LBP is an enlightenment invariant descriptor. The administrator can be reached out to utilize neighborhoods of various sizes [35].

Another expansion to the first administrator is the definition of alleged uniform examples, which can be utilized to lessen the length of the component vector and execute a straightforward rotationinvariant descriptor [35]. A LBP is called uniform if the paired example contains at most two bitwise advances from 0 to 1 or the other way around when the bit design is viewed as roundabout. The quantity of various names of LBP diminishes from 256 to only 10 in the uniform example.

The standardized histogram of the LBPs (with 256 and 10 receptacles for non-uniform and uniform administrators, individually) is utilized as a component vector. The suspicion basic the calculation of a histogram is that the dissemination of examples matters, yet the correct spatial area does not. In this manner, the benefit of separating the histogram is the spatial invariance property. To examine if area matters to our concern, we additionally executed the technique exhibited in [36], for confront acknowledgment, where the LBP filtered pictures are similarly partitioned in rectangles and their histograms are connected to shape a final include vector.

In this investigation, the histogram of the LBP picture was further reducedusing PCA, and a SVM with RBF portion is utilized as the classifier. Additionally to the CNN-Random models, the hyperparameters, for example, the quantity of PCA parts and SVM regularizationparameter,where discovered utilizing a broad beast forcesearch onmore than2000combinations.

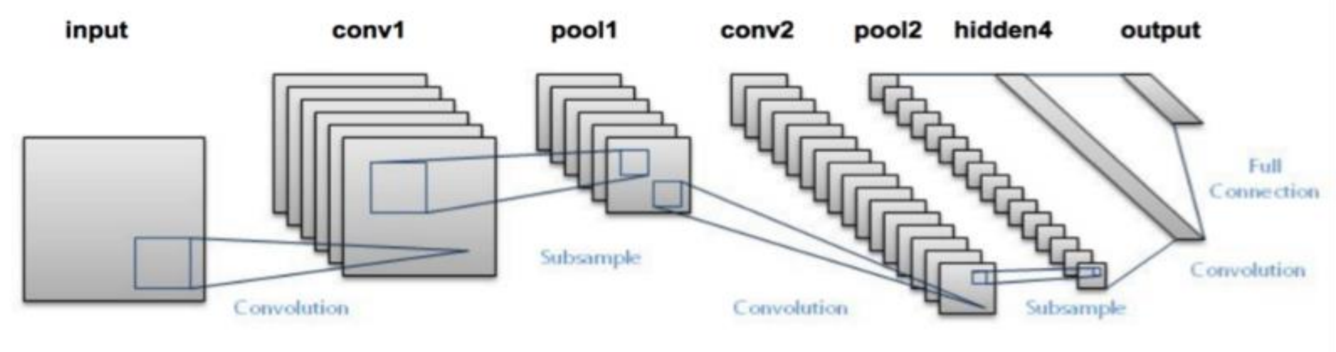

Fig 3: Lenet Model

D. Increasing the Classifiers Generalization Through Dataset Augmentation

Growth is a method that includes artificially making marginally modified tests from the first ones. By utilizing them amid preparing, it is normal that the classifier will turn out to be more strong against little varieties that might be available in the information, compelling it to learn bigger (and perhaps more vital) structures. It has been effectively utilized as a part of PC vision benchmarks, for example, in [19], [37], and [38]. It is especially appropriate to out-ofcore (calculations that needn't bother with every one of the information to be stacked in memory amid preparing, for example, CNNs prepared with Stochastic Gradient Descent. Our dataset expansion execution is like the one displayed in [19]: from each picture of the dataset five littler pictures with 80% of each measurement of the first pictures are removed: four patches from each corner and one at the middle. For each fix, level reflections are made. Subsequently, we get a dataset that is 10 times bigger than the first one: 5 times are because of interpretations and 2 times are because of reflections. At test time, the classifier makes an expectation by averaging the individual forecasts on the ten patches.

III. EXPERIMENTS

A. DATASETS

The datasets gave by the Liveness Detection Competition (LivDet) in the times of 2009 [39], 2011 [40], and 2013 [41] are utilized as a part of this examination.

LivDet 2009 includes very nearly 18,000 pictures of genuine and phony fingerprints procured from three distinct sensors (Biometrika FX2000, Crossmatch Verifier 300 LC, and Identix DFR 2100). Counterfeit fingerprints were gotten from three distinct materials: Gelatin, Play Doh, and Silicone. Roughly 33% of the pictures of the dataset are utilized for preparing and the staying for testing.

LivDet 2011 includes 16,000 pictures procured from four distinct sensors (Biometrika FX2000, Digital 4000B, Italdata ET10, and Sagem MSO300), each having 2000 pictures of phony and genuine fingerprints. Half of the dataset is utilized for preparing and the other half to test. Counterfeit fingerprints were acquired from four unique materials: Gelatin, Wood Glue, Eco Flex, and Silgum.

LivDet 2013 involves 16,000 pictures procured from four distinct sensors (Biometrika FX2000, Crossmatch L SCAN GUARDIAN, Italdata ET10, and Swipe), each having roughly 2,000 pictures of phony and genuine fingerprints. Half of the dataset is utilized for preparing and the other half to test. Counterfeit fingerprints were acquired from five unique materials: Gelatin, Latex, Eco Flex, Wood Glue, and Modasil.

In all datasets, the genuine/counterfeit fingerprint proportion is 1/1 and they are similarly circulated amongst preparing and testing sets. The sizes of the pictures fluctuate from sensor to sensor, going from 240×320 to 700×800 pixels, however they were altogether resized by the information size of the pre-prepared models, which is 224×224 for the CNN-Alexnet model and 227×227 pixels for the CNN-VGG model.

B. PERFORMANCE METRICS

The characterization comes about were assessed by the Average Order Error (ACE), which is the standard metric for assessment in LivDet rivalries. It is characterized as

$$\text{Expert} = \text{SFPR} + \text{SFNR} /2$$

where SFPR (Spoof False Positive Rate) is the level of misclassified live fingerprints and SFNR (Spoof False Negative Rate) is the level of misclassified counterfeit fingerprints.

C. IMPLEMENTATION DETAILS

CNN-VGG and CNN-Random were prepared utilizing the Caffe bundle [42], which gives quick CPU and GPU usage and an easy to understand interface in Python. For the CNN-Random and LBP models, we composed an enhanced crossvalidation/network scan calculation for picking the best mix of hyper-parameters, in which every component of the pipeline is processed just when its preparation information is changed (the term component alludes to activities, for example, preprocessing, highlight extraction, dimensionality lessening or classification). This modification speeded-up the approval stage by roughly 10 times, despite the fact that the pick up can extraordinarily fluctuate as it relies upon the component composes and number of hyper-parameters picked. An imperative part of this work is that the calculations were keep running on cloud benefit PCs, where the client can lease virtual PCs and pay just for the hours that the machines are running. To prepare the calculations, we utilized the GPU cases that enabled us to run dataset enlarged experiments in a couple of hours; utilizing traditional CPUs the preparation would take weeks.

IV. RESULT AND DISCUSSIONS

The models utilized as a part of this examination, we additionally demonstrate the error rate of the cutting edge technique for each dataset, of which a large portion of them were found in the aggregation made by [43]. As remarked by [43], most methods have issues in this dataset. For instance, the LBP presents mistake rate near zero at approval time and around half at test time. It can be seen from LivDet 2013 rivalry comes about that this dataset is especially difficult to sum up, since nine of the eleven members introduced error rates more prominent than 45%. In spite of these outcomes, CNN models perform extremely well in this dataset, with error rates between 3.2%-4.7%. It is vital to feature that CNN-Random required a comprehensive hyper-parameter finetune (number of layers, filter measure, number of filters, and so forth.) so as to get a model with great precision.

The models of CNN-Alexnet and CNN-VGG, which were at that point precisely chose for the ImageNet protest discovery errand, are sufficiently general to be reused for the finger print liveness identification assignment and yield fantastic exactness. Another fascinating viewpoint is that theCNN-VGG performed better than the CNN-Alexnet in both protest location from ILSVRC-2012 and finger print liveness discovery undertakings. This proposes facilitate changes in models for question acknowledgment can be connected to expand precision in fingerprint liveness discovery.Our best model achieves an overall rate of 98.1% of correctly classified samples—a relative improvement of 13.7% in test error when compared with the best previously published results.

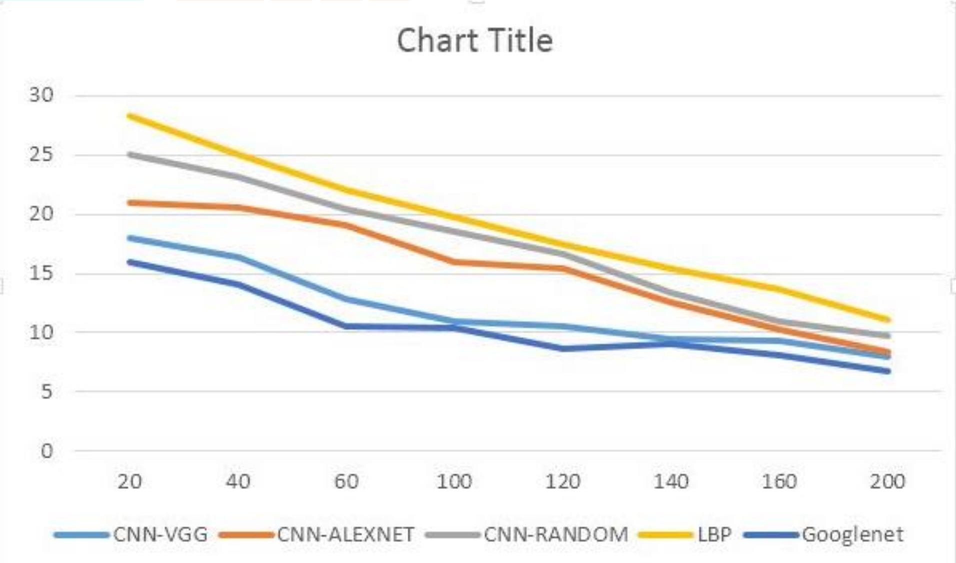

Fig 4: Accuracy rate of models used

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V. CONCLUSION

Convolutional Neural Networks were utilized to identify false versus genuine fingerprints. Pre-prepared CNNs can yield best in class comes about on benchmark datasets without requiring engineering or then again hyper parameter choice. We additionally demonstrated that these models have great exactness on little preparing sets (˜400 tests). Furthermore, no errand particular hand-built system was utilized as in traditional PC vision approaches.

Regardless of the contrasts between pictures procured from diverse sensors, we demonstrate that preparation a solitary classifier utilizing all datasets enhances precision and strength. This recommends the exertion required to plan a liveness identification framework, (for example, hyper-parameters calibrating) can be essentially decreased if distinctive datasets (and obtaining gadgets) are joined amid the preparation of a solitary classifier. Furthermore, the pre-prepared systems indicated more grounded speculation capacities in cross-dataset tests than CNN with irregular weights and the exemplary LBP pipeline.

Dataset growth assumes a critical part in expanding exactness and it is additionally easy to execute. We propose that the technique ought to dependably be considered for the preparation what's more, forecast stages if time isn't a noteworthy concern. We additionally report great exactness on little preparing sets (400 examples) utilizing these huge pretrained systems. Our best model accomplishes a general rate of 98.1% of accurately classified tests—a relative change of 13.7% in test blunder when contrasted and the best already distributed outcomes.Given the promising outcomes gave by the procedure, more composes of picture changes ought to be incorporated, for example, shading control and numerous scales portrayed in [44] and [45].

REFERENCES

[1] Rodrigo Frassetto Nogueira, Roberto de Alencar Lotufo, and Rubens Campos Machado, “Fingerprint Liveness Detection Using Convolutional Neural Networks” IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 11, NO. 6, JUNE 2016

[2] J. Galbally, F. Alonso-Fernandez, J. Fierrez, and J. Ortega-Garcia, “A high performance fingerprint liveness detection method based on quality related features,” Future Generation Computer Systems, vol. 28, no. 1, pp. 311–321, 2012.

[3] Y. Chen, A. Jain, and S. Dass, “Fingerprint deformation for spoof detection,” in Biometric Symposium, 2005, p. 21.

[4] B. Tan and S. Schuckers, “Comparison of ridge-and intensity-based perspiration liveness detection methods in fingerprint scanners,” in Defense and Security Symposium. International Society for Optics and Photonics, 2006, pp. 62 020A–62 020A.

[5] P. Coli, G. L. Marcialis, and F. Roli, “Fingerprint silicon replicas: static and dynamic features for vitality detection using an optical capture device,” International Journal of Image and Graphics, vol. 8, no. 04, pp. 495–512, 2008.

[6] P. D. Lapsley, J. A. Lee, D. F. Pare Jr, and N. Hoffman, “Anti-fraud biometric scanner that accurately detects blood flow,” Apr. 7 1998, uS Patent 5,737,439.

[7] A. Antonelli, R. Cappelli, D. Maio, and D. Maltoni, “Fake finger detection by skin distortion analysis,” Information Forensics and Security, IEEE Transactions on, vol. 1, no. 3, pp. 360–373, 2006.

[8] D. Baldisserra, A. Franco, D. Maio, and D. Maltoni, “Fake fingerprint detection by odor analysis,” in Advances in Biometrics. Springer, 2005, pp. 265–272.

[9] A. K. Jain, Y. Chen, and M. Demirkus, “Pores and ridges: Highresolution fingerprint matching using level 3 features,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 29, no. 1, pp. 15–27, 2007.

[10] D. Gragnaniello, G. Poggi, C. Sansone, and L. Verdoliva, “Fingerprintliveness detection based on weber local image descriptor,” in Biometric Measurements and Systems for Security and Medical Applications (BIOMS), 2013 IEEE Workshop on. IEEE, 2013, pp. 46–50.

[11] ——, “Local contrast phase descriptor for fingerprint liveness detection,”Pattern Recognition, vol. 48, no. 4, pp. 1050–1058, 2015.

[12] R. Frassetto Nogueira, R. de Alencar Lotufo, and R. Campos Machado, “Evaluating software-based fingerprint liveness detection using convolutional networks and local binary patterns,” in Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings, 2014 IEEE Workshop on. IEEE, 2014, pp. 22–29.

[13] D. Menotti, G. Chiachia, A. Pinto, W. Robson Schwartz, H. Pedrini, A. Xavier Falcao, and A. Rocha, “Deep representations for iris, face, and fingerprint spoofing detection,” Information Forensics and Security, IEEE Transactions on, vol. 10, no. 4, pp. 864–879, 2015.

[14] X. Jia, X. Yang, K. Cao, Y. Zang, N. Zhang, R. Dai, X. Zhu, and J. Tian, “Multi-scale local binary pattern with filters for spoof fingerprint detection,” Information Sciences, vol. 268, pp. 91–102, 2014.

[15] L. Ghiani, G. L. Marcialis, and F. Roli, “Fingerprint liveness detection by local phase quantization,” in Pattern Recognition (ICPR), 2012 21st International Conference on. IEEE, 2012, pp. 537–540.

[16] S. B. Nikam and S. Agarwal, “Local binary pattern and wavelet-based spoof fingerprint detection,” International Journal of Biometrics, vol. 1, no. 2, pp. 141–159, 2008.

[17] L. Ghiani, A. Hadid, G. L. Marcialis, and F. Roli, “Fingerprint liveness detection using binarized statistical image features,” in Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on. IEEE, 2013, pp. 1–6.

[18] P. Y. Simard, D. Steinkraus, and J. C. Platt, “Best practices for convolutional neural networks applied to visual document analysis,” in null. IEEE, 2003, p. 958.

[19] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.

[20] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein et al., “Imagenet large scale visual recognition challenge,” International Journal of Computer Vision, pp. 1–42, 2014.

[21] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” CoRR, vol. abs/1409.1556, 2014.

[22] S. Karayev, M. Trentacoste, H. Han, A. Agarwala, T. Darrell, A. Hertzmann, and H. Winnemoeller, “Recognizing image style,” arXiv preprint arXiv:1311.3715, 2013.

[23] Y. LeCun et al., “Generalization and network design strategies,” Connections in Perspective. North-Holland, Amsterdam, pp. 143–55, 1989.

[24] L. Wan, M. Zeiler, S. Zhang, Y. L. Cun, and R. Fergus, “Regularization of neural networks using dropconnect,” in Proceedings of the 30th International Conference on Machine Learning (ICML-13), 2013, pp. 1058–1066.

[25] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.

[26] Y.-L. Boureau, J. Ponce, and Y. LeCun, “A theoretical analysis of feature pooling in visual recognition,” in Proceedings of the 27th International Conference on Machine Learning (ICML-10), 2010, pp. 111–118.

[27] M. D. Zeiler and R. Fergus, “Stochastic pooling for regularization of deep convolutional neural networks,” arXiv preprint arXiv:1301.3557, 2013.

[28] Y. LeCun, K. Kavukcuoglu, and C. Farabet, “Convolutional networks and applications in vision,” in Circuits and Systems (ISCAS), Proceedings of 2010 IEEE International Symposium on. IEEE, 2010, pp. 253–256.

[29] K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun, “What is the best multi-stage architecture for object recognition?” in Computer Vision, 2009 IEEE 12th International Conference on. IEEE, 2009, pp. 2146– 2153.

[30] A. Saxe, P. W. Koh, Z. Chen, M. Bhand, B. Suresh, and A. Y. Ng, “On random weights and unsupervised feature learning,” in Proceedings of the 28th International Conference on Machine Learning (ICML-11), 2011, pp. 1089–1096.

[31] T. G. Dietterich, “Approximate statistical tests for comparing supervised classification learning algorithms,” Neural computation, vol. 10, no. 7,pp. 1895–1923, 1998.

[32] B. T. Polyak, “Some methods of speeding up the convergence of iteration methods,” USSR Computational Mathematics and Mathematical Physics, vol. 4, no. 5, pp. 1–17, 1964.

[33] I. Sutskever, J. Martens, G. Dahl, and G. Hinton, “On the importance of initialization and momentum in deep learning,” in Proceedings of the 30th international conference on machine learning (ICML-13), 2013, pp. 1139–1147.

[34] A. Hadid, M. Pietik¨ainen, and T. Ahonen, “A discriminative feature space for detecting and recognizing faces,” in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, vol. 2. IEEE, 2004, pp. II–797.

[35] T. Ojala, M. Pietik¨ainen, and T. M¨aenp¨a¨a, “Multi resolution gray-scale and rotation invariant texture classification with local binary patterns,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 24, no. 7, pp. 971–987, 2002.

[36] T. Ahonen, A. Hadid, and M. Pietik¨ainen, “Face recognition with local binary patterns,” in Computer vision-eccv 2004. Springer, 2004, pp. 469–481.

[37] D. C. Cires¸an, U. Meier, J. Masci, L. M. Gambardella, and J. Schmidhuber, “High-performance neural networks for visual object classification,” arXiv preprint arXiv:1102.0183, 2011.

[38] D. Ciresan, U. Meier, and J. Schmidhuber, “Multi-column deep neural networks for image classification,” in Computer Vision and Patter Recognition (CVPR), 2012 IEEE Conference on. IEEE, 2012, pp. 3642– 3649.

[39] G. L. Marcialis, A. Lewicke, B. Tan, P. Coli, D. Grimberg, A. Congiu, A. Tidu, F. Roli, and S. Schuckers, “First international fingerprint liveness detection competitionlivdet 2009,” in Image Analysis and Processing–ICIAP 2009. Springer, 2009, pp. 12–23.

[40] D. Yambay, L. Ghiani, P. Denti, G. L. Marcialis, F. Roli, and S. Schuckers, “Livdet 2011fingerprint liveness detection competition 2011,” in Biometrics (ICB), 2012 5th IAPR International Conference on. IEEE, 2012, pp. 208–215.

[41] L. Ghiani, D. Yambay, V. Mura, S. Tocco, G. L. Marcialis, F. Roli, and S. Schuckcrs, “Livdet 2013 fingerprint liveness detection competition 2013,” in Biometrics (ICB), 2013 International Conference on. IEEE, 2013, pp. 1–6.

[42] Y. Jia, “Caffe: An open source convolutional architecture for fast feature embedding,” 2013.

[43] D. Gragnaniello, G. Poggi, C. Sansone, and L. Verdoliva, “An investigation of local descriptors for biometric spoofing detection,” Information Forensics and Security, IEEE Transactions on, vol. 10, no. 4, pp. 849– 863, 2015.

[44] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” arXiv preprint arXiv:1409.4842, 2014.

[45] A. G. Howard, “Some improvements on deep convolutional neural network based image classification,” arXiv preprint arXiv:1312.5402,2013.