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HAND WRITTEN SIGNATURE RECOGNITION USING DEEP LEARNING NETWORKS

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Abstract

Hand Written Signature Recognition is an indispensable biometric method for plan to see whether or not accessible mark is truly phony or genuine. It's obligatory in forestalling adulteration of reports in checking the lawfulness of archives like drafts, identification, visa and modern financial transactions. Our examination point is to automatize the technique for written by hand Signature recognition by applying Convolutional Neural Network. Proposed model depends on VGG16 plan, and that we utilized our own dataset to prepare our model with move learning. Once characterizing whether or not a given mark was falsification or genuine, we will quite often arrive at the exactness of almost 100% with utilization of my restrictive dataset. We tend to also performed many investigations changing the classes of preparing information and forecast undertaking to make it extra pertinent to genuine applications, that our procedure seems promising.

Keywords: Hand Written Signature**,** Convolutional Neural Network, FRR, FAR, Support Vector Machine.

I. Introduction

Biometric verification is that the strategy for corroborative the personality of individuals upheld unmistakable organic attributes. It's become present typical for admittance to high security frameworks. Current procedures in AI and insights have took into account dependable mechanization of the large number of those undertakings (face, finger impression, iris). Among the different errands utilized for biometric acknowledgment, is transcribed mark confirmation that expects to see whether or not given written by hand mark is real or counterfeit. Transcribed hand written Signature is need of hour in taking care of adulteration in archives in fluctuated money related, lawful and different modern exchanges. The errand presents numerous particular troubles: high intra-class changeability (a singular's mark could shift significantly day-today), huge worldly variety (mark could adjustment absolutely over the long run), and high internal classification closeness (fabrication normally, choose to be vague from genuine marks as could really be expected).There exist two arrangements of mark confirmation: on-line and disconnect. on-line confirmation needs partner degree electronic mark framework that gives data like the pen's point, height point, and strain at each time-step of the gesture based communication, conversely, disconnected check utilizes alone second visual (pixel) data non heritable from filtering marked records. Though on-line frameworks offer a ton of data to check character, they're less adaptable and could exclusively be utilized in certain unique circumstances (e.g., managing approval) because of they need explicit information frameworks. We expect to make partner degree disconnected biometric recognizable proof framework utilizing a deep Neural Network. Our research centers around building frameworks prepared data with variable levels of information, also exploring different avenues regarding very surprising objective capacities to get ideal blunder rate.

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II. Related Work

Currently, researchers are trying to find various techniques to improve hand written signature verification and normalized standard for performance analysis. Data-intensive method invented by Hirunyawanakul et. al [2], converted signature information of image data into numerical value in accordance color intensity of gray scale. On the far sides the non-online distinction, there are two additional characterises that outline the task of signature authentication, it will discuss with a"fraud manifestation" and"creater-dependence". The fraud manifestation of the task is decided on what sorts of hand written signature framework is trained on. Some author train on frauds as well as real hand written signatures, however take a look at on totally different forgeries and real signatures throughout take a look at, some train on forgeries for identities that exist only within the coaching set (then test on forgeries and real signatures for novel identities), some authors do not use forgeries in any respect throughout coaching. it is value noting that solely the afterward twain tasks are cheap for sensible application. That is, whereas a system might have access to a development set that features forgeries, it is unlikely that forgeries are often non inheritable for all users of that system. We have got trained systems for the primary 2 of those varieties. Within the experiments section, we have a tendency to detail specifically however we have a tendency to use the coaching and take a look at knowledge to accomplish every task. The creator-dependence distinction refers as to if the model encompasses a totally different classifier for every identity, or one classifier for all identities. Creator-dependent method that at a lot of common within the literature, use a distinct classifier for every user. At take a look at time, the approach is given the identity of the hand written signatures that it is testing credibility. Creator-independent models use one classifier for all identities. We have got developed each creator-dependent and creator-independent methods in research. Most proposed methods within literatures use express trait extraction, as well as geometry [9], graph geometry [10], directions [11], riffles [12], shadows [13], and textures [14] options. Solely in current time of features to learn have been explored [15]. It has a tendency to introduce fresh pixels to the network, holding the deep learning the relevant options for hand written signature verification.

Fig 1 Hand Written Signatures

The mark confirmation writing incorporates many examples of HMMs based Neural Networks, SVM and different AI methods. In 2012, Khalajzadeh et al. [15] involved deep learning networks for written by hand written signatures confirmation, that will be that the exclusively report of CNNs being utilized inside the disconnected mark check writing. Unfortunately, the paper incorporates practically zero information with respect to their procedure (for example fraud openness, creator reliance). Upheld their explanation, we tend to expect model is prepared on frauds and real marks for entire

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IDs, as are frequently contrasted and our add our fundamental investigation. There results exclusively report a middle of ninety nine.86 for approval execution, and mean square blunder, making it problematic to totally contrast to proposed model with others.

III. Strategies

Convolutional Neural Networks (CNNs) have all around attempted undefeated as of late at a larger than usual scope of picture handling based AI undertakings. a few unique methodologies of playing such undertaking rotate around a technique for highlight extraction, during which hand-picked choices removed from image is taken care of by a classifier to settle on the characterization result. These cycles will exclusively has hearty in light of the fact that the picked choices, which routinely take monstrous measures of care and energy to develop. Conversely, in a CNN, the choices took care of into a definitive direct classifier are all gained through the dataset. A deep learning network comprises for assortment of layer, beginning at the crude image pixel, that every play out a easy calculation of feed to outcome to future layer with a definitive outcome being taken care of to a direct classifier. The layers' calculations ar upheld assortment of boundaries that are learned through the technique for back engendering, during which for each boundary, the slope of the characterization misfortune with connection to that boundary is figured and furthermore the boundary is refreshed determined to limit the misfortune work. Explicitly anyway updates are finished and what is misfortune work is adapt hyper parameters of the organization, referenced in extra info underneath. A great deal of subtleties on backpropagation, see [5].

The plan of a deep network figures out which rate layers it's, how everything about layers is treating, the manner by which layer is associated with every unique, selection a fair plan is having vital to undefeated learn to deep networks. For primary coaching assignments, It tend to utilized the VGG-16 networks [6]. This organization has total sixteen layers with learning parameter. All layers having the resulting types, fully associated Layer: completely associated layer applied a change of it's bits of feedbacks. Numerically, a fully associated layer from m contribution to y yields fills in as follows:

$$f(x) = W_{tx}Wtx + b \tag{1}$$

A fully-connected layer, each result depends on each input consistent with burden matrix W_t, a learning parameter. Output additionally rely upon a bias terms that is learnable. However, does not rely upon the inputs. ReLU Nonlinearity: The corrected linear measures could be a ordinarily used activation operate once fully associated layer. This layer utilised the subsequent computing of input X:

$$F(X) = Max(0, X) \tag{2}$$

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Highest value taken element-wise. ReLU layers not having learning boundaries. ReLU activation function regularly utilized in current deep learning networks rather than conceivable initiation capacities, for example, sigmoid or tanh for a considerable time duration. One of explanation is that calculation has exceptionally basic, saving time during preparation that would be used for processing exponential for sigmoid or tanh. ReLU neuron additionally do not become immersed to good information values, meaning their inclination does not evaporate to null while getting such qualities. This permits the neurons to keep learning in situations where other enactment capacities would have disappearing slopes. Be that as it may, on the grounds that the angle of a ReLU neuron is null for false sources of info, it is additionally feasible for neurons to quit learning in situations where the feedback never creates positive qualities. The nonlinearity of Softmax function shows up of last layer of the neuron organization shows last class values those may be taken care of into the misfortune work or yielded during test. It has no learning parameter. These values has understanding as the neuron organization's assessed probability for each types. It can be taken note for every one of result value delivered by softmax function work addition. Numerically, ith group likelihood $f_j(z)$ is processed as shown,

$$f_j(z) = \frac{e_j^z}{\sum_k e_k^z} \tag{3}$$

Utilizing Soft ax to process class scores is an alluring choice in light of its simplicity of understanding.

VGG16 layers operates an info picture by sliding over on various little kernel across every useful areas and producing the dab result of the kernel and the picture on every locale. This are like completely associated layer, yet with constraints on which input neurons are associated with which produced. In particular, yields are simply associated with contribution of a few district, and all loads for each kernel are integrated rather than being allowed to advance autonomously. The learning boundaries for a processing ayer are the loads of each kernel and single inclination an incentive for each kernel. Processing layers adapt itself normally to comprehensive of image, in which we often need to remove highlights by taking a care at little region of a picture, where it do not mind precisely in the picture the element. At the instance, the face as yet a face by any case f where in the picture it is. Our design utilizes 2x2 kernels, with more kernels utilized every layer as the organization get further yields**.**

Pooling layer: The pooling layer is also called a down sample layer. There are many types of layer option such as average, minimum and max pooling. However most preferred method is max pooling layer. Pooling process has no learning elements. Pooling layer reduces both the length and width of the subject image as it passes through to the next stage. In networks with maximum pooling layer, the input length and width reduced as the subject image is passed on through the designed network, and the number of filters likely to go-up. This be in tune with to processing the subject image at a next level of abstraction in which features associate to bigger area of input image.

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Dropout layer: In order to avoid the overfitting dropout layer is used. It is a non-deterministic nonlinearity used in most of the current neural networks. A dropout layer is used to contain the switching functions to random pick-up neurons during each iteration of the model training. The optimal value of dropout is adaptable hyper parameters of the deep learning network. Discard value can be explained as to prevent the neurons to learn the features which are relevant only. Discard value during training phase of the network for many ways of computing a desired output.

Preparing the Network

Unfortunate work, it picked the standard Category of Cross-Entropy misfortune of L2 regularization, is registered by the results of the last Soft ax classifier. Assuming that x is the outcome from the Soft ax classifier for a selected preparation of main item, the irregular misfortune. This is a standard misfortune work for CNN's. One significant element of this misfortune work is that not normal for different decisions, for example, the Hinge Loss work, it doesn't become happy by output that may be "sufficient" and tries to push the class value increasingly close flawlessly, relating every likelihood weight being allocated to right group. Utilizing angle of this misfortune work, it is updated every boundaries of the organization utilizing the momentum update. The thinking for utilizing current specific update strategy is clarified in our Results segment. This update monitors a variable "v" that is a component of the greatness of past updates, permitting the learning rate to rely upon this variable. This kind of update is better lenient to various benefits of learning value and will in general merge somewhat rapidly, as it can adjust over the long haul in light of how rapidly the boundaries are evolving.

A. Transfer learning

Deep learning network is a large neuron organization with a many number of learning variables. Actually, preparing an organization this enormous without any preparation requires a huge dataset and admittance to significant computational assets. Notwithstanding, the issue can be deflected by utilizing likeness between various subject image datasets. In particular, the best sensible subject picture grouping job, low-level elements learned by the initial not many layers of an organization can be in general the equivalent no matter what is the dataset. It implies that there can instate our neuron organization with boundary value gained by an alternate dataset and expected that the qualities of the primary layers of the organization function admirably not being prepared. This cycle is known as move learning. We introduced our model with the pretrained loads and permitted just the completely associated layer toward finish to prepare, keeping the deep learning layer fix all through preparing (it is a choice all come to base on to test various choices, get output of additional conversation).

B. Networks Comparison

In last experiment, it utilize a technique proposed in [7] for picture fix correlation. The research proposed a few model for picture fix correlation pseudo random, and two-channel organizations. In the two-channel organization, more than one images are stacked (for example every image fills in as a kernel for the composite, matched picture) contribution to a deep learning network. The deep learning network then, at that point, prompts a full associated straight choice layer with one result that demonstrates the comparability of the 2 patches. They observed the two-channel

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network beats the applied structures. Further insights concerning variation in the results area. Coming up next is a sketch of a 2-channel design:

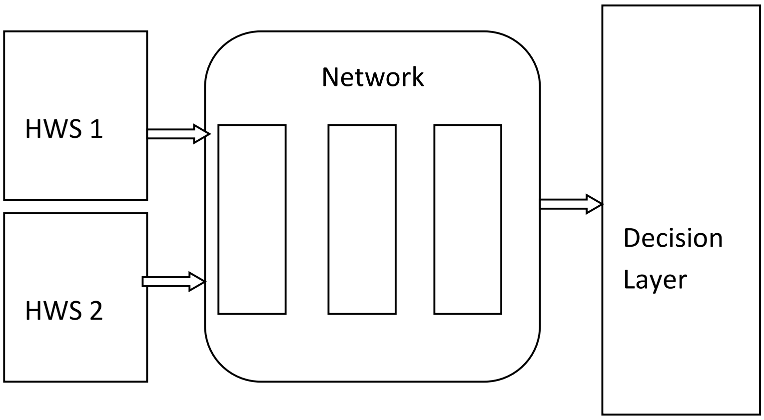

Figure 2. Network for image patch comparison

Preparing set contains 500 pictures for 15 IDs, with around 25 authentic marks, thirty fabrications in every identity. Two test sets incorporate a "reference" and addressed sets, where the reference is familiar to certifiable marks. The addressed marks are either veritable or fashioned. The dataset 1 test set has 50 identities, every 15 References mark and around 30 addressed marks. The dataset 1 testing set had 15 identities, each with around 10 Reference marks and around 55 addressed marks. We adjusted to the recommended preparing testing split for our last analysis, yet changed the parts to expand the quantity of models in our preparation set for different undertakings.

IV. Results

During preparing and model alignment, we will quite often order out a check set that wasn't tried on till a definitive accommodation of our venture. we will more frequently not report exactness on this set furthermore as on an approval set, that we watch out for won't to adapt hyper parameter as it tend to iterate on proposed technique. The model we will generally examine the best one that accomplished the least complex exhibition on the approval set, and that we run it best technique on actually take a look at set to achieve the outcomes for the really take a look at set. Each of our assignments include the test-time conduct of ordering whether or not a given mark is strong or genuine. It will generally assess our exhibition exploitation and measurements: arrangement precision, FAR, and FRR. These are characterized as follows, veritable marks are thought of" true" models:

$$\text{Accuracy} = \frac{\text{true positive+true negative}}{\text{numerical\_data}} \tag{4}$$

$$\text{FAR} = \frac{\text{false\_ negative}}{True_{Positives}+false\_negatives} \tag{5}$$

$$\text{FRR} = \frac{\text{false\_ positives}}{\text{false}_{\text{positive}}+\text{true\_negative}} \tag{6}$$

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Higher value is good, and lower FAR and FRR are good. Measurements can deciphered by various ways, yet it is doubtful it in application it is generally critical to accomplish less FAR value, as decent hand written Signature confirmation framework ought falsifications through, while incidentally arranging a real signature as a fraud is to a lesser degree an issue since one can just request that the individual sign their mark once more.

First assignment was for preparation of a DNNs to perceive whether individual marks are produced or veritable, having visible instances of twain manufactured authentic forms of equivalent individual's mark at the time of preparing. Undertaking mark all informative items in our ECIL restrictive Datasets as certified / fashioned, disposing character underwriter. Train one organization of marks for all characters together. For every language, every one of the information for that linkage is parted in preparing, approval, and test data information arbitrarily, meaning approval and test information comprise of fresh duplicates of marks of similar individuals whose marks are in the preparation set. For both dataset 1 and dataset 2, we put 70% of information in preparation set and 20% in every one of approval and test data sets.

Outputs are tabulated in the table below:

Table 1: Observation for different Test Database

Categories	Dataset1	Dataset 2	Our Result
Accuracy (Validation)	97%	95%	98%
FAR (Validation)	3.6%	4.7%	3.5%
FRR (Validation)	3.6%	5.6%	3.5%
Accuracy (Test)	94%	88%	95%
FAR (Test)	13.32%	8.2%	13.50%
FRR (Test)	3.13%	18.2%	3.50%

Our objectives while tuning the organization was to accomplish the most ideal grouping exactness, FAR and FRR values in dataset 1. Utilizing those equivalent boundaries, we use, at that point, tried on the dataset 2 to accomplishing the outcomes above. This interaction clarifies to some degree why the outcomes for the dataset 2 are altogether lower than dataset 1. Checking out the plots preparing and approval misfortune underneath, we presume that it has over fit our preparation set to all things considered a little degree. Whenever it train for longer for 20 ages, the preparation misfortune doesn't turn out to be essentially not exactly the approval misfortune until after approximately 15-20 ages, and after this point, preparing misfortune keeps on diminishing however approval misfortune starts to increment. Now, approval exactness tops too and afterward starts to reduce. Our test correctness is in similar ballpark as the approval exactness however are rather lower. It tuned a few hyper parameter utilizing the approval dataset, including learning value, formalization consistent, and number of layer to prepare. Since the settings it picked mirrored the

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finest execution on approval on set, all things considered, the hyperparameters were somewhat fitting noise in the approval set.

Significant part of preparation for which boundary updated calculation we utilise. It was considered various different boundary update plans as preliminaries. We tried different update rules on our primary undertaking. Obviously, SGD was reliably more slow to unite than any of different techniques. We experienced difficulty observing hyperparameters that got Adam to meet, despite the fact that it's conceivable that this is on the grounds that we didn't attempt an adequate number of blends. This outcome was astounding since Adam is frequently suggested as an update rule rather than more straight forward strategies, however we couldn't get Adam to accomplish similar accuracy. Last decision of update calculation was Momentum method, which performed in much the same way to the next best calculations as far as approval precision and which was alluring because of its effortlessness. The accompanying shows approval precision over the long haul with different update calculations:

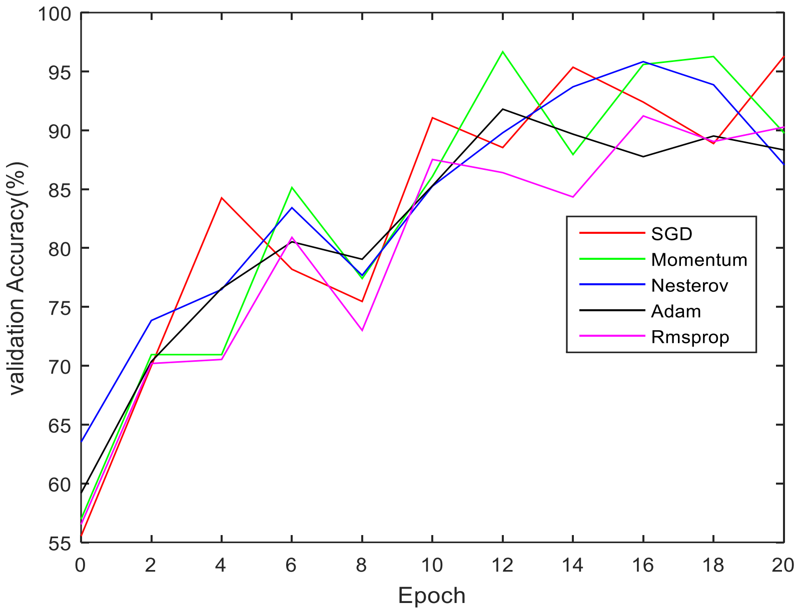

Fig 4. Accuracy on test data for every type of parameter tune.

Undertaking, most noteworthy method utilized L2 regularization along with regularization consistent of 2e3. We tend to establish this hyper parameter utilizing worst-to-best inquiry approach and picking values that made the most straightforward approval exactness. Utilizing a finite regularization consistent was fundamental for our outcomes, as running the organization with no regularization produces serious over fitting. We tend to utilized a learning value of 1e3, that was the revert learning rate for momentum method updating. It tend to directed numerous preparation phases runs with values near this on each side anyway neglected to see higher outcomes.

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Training Plots

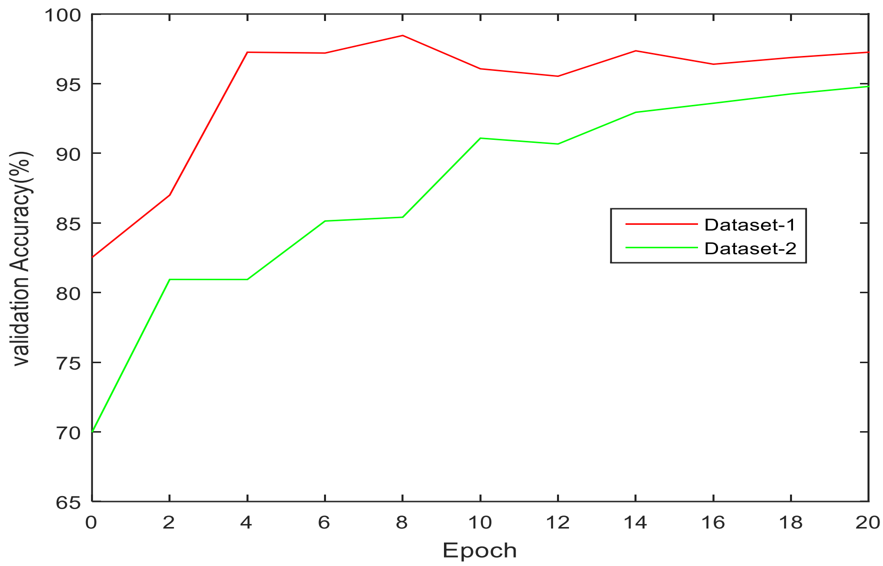

Fig 5. Accuracy on each Epoch

We can get large outcomes on fundamental undertaking because of the check data looks like the instructing data, in this it contains marks from indistinguishable people. We tend to needed to extend our outcomes to harder errands inside the datasets were less comparative. Such errand is to actually look at the organization gathering marks altogether fully unexpected person than the training data set. For present analysis, it will quite often part data set into training, test, and approval data sets consist of 80th, 10%, and 100% of the information severally. The qualification, in any case, is that the approval and check sets comprise exclusively of marks by fresh individuals and imitations by fresh people that don't appear to be gift inside the training set. An organization that is flourishing at this errand would advance some type of information in regards to trademark marks from their frauds that is valid across the marks, everything being equal. It's indistinct whether or not such data exists, and therefore we tend to neglected to anticipate awfully elite execution at this errand. For this errand, our most prominent model utilized L2 regularization via a formalization steady on 2x2, a learning pace of 1e3, and a drop out value of 0.5.

Outputs are tabulated below:

Table 2: Observation for proposed method

Category for Validation & test	**Existing 1**	**Our Results**
Accuracy	73%	74%
FAR	22.2%	22.5%
FRR	28.3%	28.8%
Accuracy	76%	78%
FAR	28.6%	28.8%
FRR	21.8%	21.3%

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Due to the class slant of the dataset one, a web that anticipated genuine for every mark would succeed a grouping exactness of 67 (with A such a large amount 100% and FRR of 0%). Our presentation is fairly higher than this, and our errors region unit extra similarly opened up between each styles of misclassifications. Notwithstanding, these outcomes aren't much better than shot all genuine. This implies that our organization had the option to eat up on some data that is as yet steady across the marks, all things considered, but this information was scarcely to the point of accomplishing A correctness somewhat higher than a gullible standard. Our instructing runs for this errand succumbed to over fitting. Expanding the regulation boundary and drop out share was helpful only for small increment - to huge will build, organization quit learn in any regard. Instructing for less ages was conjointly helpful to battle overfitting - our most prominent models were prepared for under five ages, and execution started to decrease forcefully once this gratitude to overfitting. Instructing misfortune kept on diminishing anyway approval misfortune started to reach out right now. it's modest to anticipate that over fitting would be a retardant with the sort of assignment, since it can clear to discover data that recognizes marks their phonies in an extremely technique that is explicit to the individual, but harder to incite this to sum up to new people. As far as arrangement precision, the outcomes from this explore region unit very little higher than shot steady, commonest classification for each single investigate model. This intends that there's insufficient information gift during this errand to make modest forecasts, at least with our CNN procedure. we not entirely settled to not proceed with this trial with the Chinese dataset, continuing on rather to an extra manageable downside elaborated beneath.

In creator-Dependent Comparison we have a tendency to train our network on genuine pairs and in genuine pairs for all identities in training set. We have a tendency to take a look at entirely on unseen IDs. Thus, the network ought to learn to inform once 2 signatures area unit constant or completely different. for every take a look at ID, there are a unit ten reference signatures that area unit famed to be real, and twenty five hand written signature, that area unit either real or fake. At take a look at time, we have a tendency to send each hand written signature in the network pair with every reference hand written signature. Thus, every questioned-reference pairing is a vote, and if the network deems that the hand written signature differs from too several of the standard signatures, it is classified as a frauds.

Table 3: Observation for test Dataset-1

Category for Validation	Dataset 1	Our Result
Accuracy	67.1%	70.1%
FAR	33.5%	33.9%
FRR	33.7%	33.9%

However, this test had equivalent outcomes to the inconspicuous characters test. Notwithstanding, our outcomes experience of exceptional blunder that offers space for trust in ongoing investigations. The accomplishment of research model differed

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significant of one identity to another. On certain identities, the model totally ordered the frauds and genuine. When our model fruitless, it really focused on fizzle for some models among that identity, commonly by either exploitation consistently genuine or cast.

V. Conclusion

We studied the problem of hand written signature authentication with the prime focus to improve the authentication accuracy by applying the novel technique of deep learning techniques. We tend to showed that convolutional neural organizations work effectively to confirm marks once permitted admittance all through instructing to tests of genuine and phony marks of an identical people whose marks square measure seen at actually look at time. we tend to then led partner try any place we tend to tried our organization on the marks of most recent people whose marks had not been found in any regard all through instructing, prompting execution very little higher than a gullible pattern on account to the inborn issue of this undertaking. We tend to organized a thoroughly fascinating arrangement for the connection of imprints that has ensure for future add signature affirmation, expressly in things any spot a maybe molded imprint is appeared differently in relation to better-known real characteristics of a picked financier. We tend to propose two bearings for future work. In the first place, admittance to a ton of assets would empower U.S. to achieve better execution on our primary undertaking. In particular, being able to mentor on a greater dataset with a ton of mark models per individual might achieve higher correctness, still as training bigger organization for a ton of ages, that we tend to couldn't do because of time and machine asset imperatives. We tend to were conjointly impacted here by the very reality that our dataset was similarly little, exclusively on the request for great many models, which it's hard to look out savvy freely out there signature datasets. The creator Dependent Comparison Task conjointly is by all accounts a promising bearing for future investigation. This assignment is tempting because of it reflects the instance of a true use of mark confirmation. However, we tend to couldn't accomplish high outcomes at this assignment, the writing on signature confirmation shows that our technique is promising. Approaching a great deal of information and a ton of machine assets would conceivably empower U.S. to accomplish more grounded outcomes at this undertaking still. With admittance to those, we'd prepare our model on bigger datasets and license a great deal of layers to mentor for a ton of ages. This disadvantage would conjointly require longer spent thoroughly normalization the organization, that we tend to were unfortunately unfit to attempt to accomplish for this drawback.

Reference

1. H. Baltzakis and N. Papamarkos. A new signature verification technique based on a two-stage neural network classifier. Engineering applications of Artificial intelligence, 14(1):95–103, February 2001.
2. Bailing Zhang. Off-line signature verification and identification by pyramid histogram of oriented gradients. International Journal of Intelligent Computing and Cybernetics, 3(4):611–630, 2010.
3. Donato Impedovo, Giuseppe Pirlo, and Rejean Plamondon. Handwritten signature verification: New advancements and open issues. In Frontiers in Handwriting Recognition, International Conference on. IEEE, 2012.

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4. J. Bromley, J. W. Bentz, L. bottou, I. Guyon, Y. LeCun, C. Moore, E. Sackinger, and R. Shah, Signature verification using a siamese time delay neural network, Int. J. Pattern Recognit. Artificial Intell., vol. 7, no. 4, pp. 669687, Aug. 1993.
5. K. Simonyan, A. Zisserman "Very Deep Convolutional Networks for Large-Scale Image Recognition" in ICLR 2015
6. S. Zagoruyko, N. Komodakis "Learning to Compare Image Patches via Convolutional Neural Networks" CVPR 2015, arXiv:1504.03641v1
7. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 38, no. 5, pp. 609–635, Sept 2008.
8. L. S. Oliveira, E. Justino, C. Freitas, and R. Sabourin, Thegraphology applied to signature verification, in 12th Conference of the International Graphonomics Society, 2005, pp. 286 290
9. M. M. Fahmy, "Online handwritten signature verification system based on dwt features extraction and neural network classification," Ain Shams Engineering Journal, vol. 1, no. 1, pp. 59 – 70, 2010.
10. P. S. Deng, H.-Y. M. Liao, C. W. Ho, and H.-R. Tyan, Wavelet-Based Off-Line Handwritten Signature Verification, Computer Vision and Image Understanding, vol. 76, no. 3, pp. 173190, Dec. 1999
11. U. A. Jain and N. N. Patil, "A comparative study of various methods for offline signature verification," 2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Ghaziabad, 2014, pp. 760–764, doi: https://doi.org/10.1109/ICICICT.2014.6781376. Google ScholarCrossref
12. N. A. Murshed, R. Sabourin, and F. Bortolozzi, A cognitive approach to off-line signature verification, International Journal of Pattern Recognition and Artificial Intelligence, vol. 11, no. 05, pp. 801825, 1997.
13. S. Garcia-Salicetti, N. Houmani, B. Ly-Van, B. Dorizzi, F. Alonso-Fernandez, J. Fierrez, J. Ortega-Garcia, C. Vielhauer, and T. Scheidat, Online Handwritten Signature Verification. London: Springer London, 2009, pp. 125– 165..
14. Debasish Jena, Banshidhar Majhi, Saroj Kumar Panigrahy, Sanjay Kumar Jena, "Improved Offline Signature Verification Scheme Using Feature Point Extraction Method" Proc, 7th IEEE Int. Conf. on Cognitive Informatics (ICCI'08) Y. Wang, D. Zhang, J. C Latombe, and W. Kinsner (Eds.) 978-1-4244-2538-9/08 2008 IEEE
15. M. Malik, M. Liwicki, A. Dengel, S. Uchida, and V. Frinken. Automatic Signature Stability Analysis and Verification Using Local Features. In Frontiers in Handwriting Recognition, Int. Conference on. IEEE, 2014