

Handwritten Hindi Character Recognition Using Layer-Wise Training of Deep Convolutional Neural Networks

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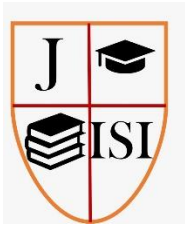
Abstract

Manually written character acknowledgment is as of now getting the consideration of scientists in view of potential applications in helping innovation for dazzle and outwardly hindered clients, human-robot collaboration, programmed information passage for business reports, and so on. In this work, we propose a strategy to perceive transcribed Devanagari characters utilizing profound convolutional neural organizations (DCNN) which are one of the ongoing procedures embraced from the profound learning network. We tested the ISIDCHAR information base gave by (Information Sharing Index) ISI, Kolkata and V2DMDCHAR information base with six distinct structures of DCNN to assess the exhibition and furthermore research the utilization of six as of late created versatile inclination strategies. A layer-wise method of DCNN has been utilized that assisted with accomplishing the most noteworthy acknowledgment exactness and furthermore get a quicker union rate. The consequences of layer-wise-prepared DCNN are great in correlation with those accomplished by a shallow strategy of high quality highlights and standard DCNN.

Keywords: handwritten character recognition, deep learning, Devanagari characters, convolutional neural network, adaptive gradient methods

1. Introduction

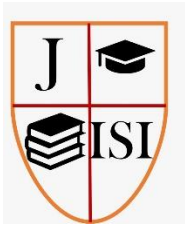
Over the most recent couple of years, profound learning approaches [1] have been effectively applied to different zones, for example, picture characterization, discourse acknowledgment, disease cell identification, video search, face location, satellite symbolism, perceiving traffic signs and person on foot recognition, and so forth. The result of profound learning approaches is likewise conspicuous, and now and again the outcomes are better than human specialists [2,3] in the previous years. The majority of the issues are additionally being re-explored different avenues regarding profound learning approaches with the view to accomplishing enhancements in the current discoveries. Various structures of profound learning have been presented as of late, for example, profound convolutional neural organizations, profound conviction organizations, and intermittent neural organizations. The whole engineering has demonstrated the capability in various zones. Character acknowledgment is one of the zones where AI methods have been broadly tested. The principal profound learning approach, which is one of the main AI procedures, was proposed for character acknowledgment in 1998 on MNIST information base [4]. The profound learning



methods are essentially made out of various concealed layers, and each shrouded layer comprises of numerous neurons, which register the reasonable loads for the profound organization. A ton of figuring power is expected to register these loads, and an incredible framework was required, which was not effectively accessible around then. From that point forward, the scientists have caused them to notice finding the method which needs less force by changing over the pictures into highlight vectors. Over the most recent couple of decades, a ton of highlight extraction methods have been proposed, for example, HOG (histogram of situated angles) [5], SIFT (scale-invariant component change) [6,7], LBP (nearby parallel example) [8] and SURF (speeded up strong highlights) [9]. These are noticeable component extraction techniques, which have been tested for some, issues like picture acknowledgment, character acknowledgment, face location, and so forth and the relating models are called shallow learning models, which are as yet famous for the example acknowledgment. Highlight extraction [10] is one kind of dimensionality decrease strategy that speaks to the significant pieces of an enormous picture into an element vector. These highlights are handmade and expressly planned by the exploration network. The strength and execution of these highlights rely upon the aptitude and the information on every scientist. There are where some fundamental highlights might be concealed by the analysts while extricating the highlights from the picture and this may bring about a high order blunder.

Profound learning rearranges the way toward handcrafting and planning highlights for a specific issue into a programmed cycle to process the best highlights for that issue. A profound convolutional neural organization has numerous convolutional layers to remove the highlights naturally. The highlights are separated just a single time in a large portion of the shallow learning models, however on account of profound learning models, numerous convolutional layers have been received to remove segregating highlights on different occasions. This is one reason that profound learning models are commonly fruitful. The LeNet [4] is a case of profound convolutional neural organization for character acknowledgment. As of late, numerous different instances of profound learning models can be recorded, for example, AlexNet [3], ZFNet [11], VGGNet [12] and spatial transformer networks [13]. These models have been effectively applied for picture order and character acknowledgment. Inferable from their incredible achievement, many driving organizations have additionally presented profound models. Google Corporation has made a GoogLeNet having 22 layers of convolutional and pooling layers on the other hand. Aside from this model, Google has likewise built up an open source programming library named Tensorflow to direct profound learning research. Microsoft additionally presented its own profound convolutional neural organization engineering named ResNet in 2015. ResNet has 152-layer network designs which made another record in location, limitation, and characterization. This model presented a novel thought of leftover discovering that makes the enhancement and the back-spread cycle simpler than the essential DCNN model.

Character acknowledgment is a field of picture handling where the picture is perceived and changed over into a machine-discernible configuration. As examined over, the profound learning approach and particularly profound convolutional neural organizations have been utilized for picture location and acknowledgment. It has additionally been effectively applied on Roman (MNIST) [4], Chinese [14], Bangla [15] and Arabic [16]



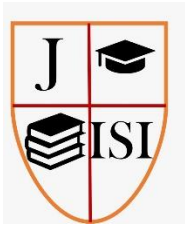
dialects. In this work, a profound convolutional neural organization is applied for transcribed Devanagari characters acknowledgment.

The primary commitments of our work can be summed up in the accompanying focuses: (1) This work is the first to apply the profound learning approach on the information base made by ISI, Kolkata. The primary commitment is a thorough assessment of different DCNN models; (2) Deep learning is a quickly creating field, which is bringing new methods that can essentially improve the presentation of DCNNs. Since these strategies have been distributed over the most recent couple of years, there is even an approval cycle for setting up their cross-area utility. We investigated the function of versatile angle strategies in profound convolutional neural organization models, and we indicated the variety in acknowledgment precision; (3) The proposed transcribed Devanagari character acknowledgment framework accomplishes a high characterization precision, outperforming existing methodologies in writing predominantly with respect to acknowledgment exactness; (4) A layer-wise method of DCNN strategy is proposed to accomplish the most noteworthy acknowledgment precision and furthermore get a quicker assembly rate.

2. Literature Review

Devanagari transcribed character acknowledgment has been explored by various element extraction strategies and various classifiers. Scientists have utilized basic, measurable and topological highlights. Neural organizations, KNN (K-closest neighbors), and SVM (Support vector machine) are basically utilized for grouping. In any case, the main exploration work was distributed by I. K. Sethi and B. Chatterjee [17] in 1976. The writers perceived the transcribed Devanagari numerals by an organized methodology which found the presence and the places of even and vertical line fragments, D-bend, C-bend, left inclination and right inclination. A directional chain code based element extraction procedure was utilized by N. Sharma [18]. A bouncing box of a character test was separated into blocks and figured 64-D course chain code highlights from each partitioned square, and afterward a quadratic classifier was applied for the acknowledgment of 11,270 examples. The writers detailed a precision of 80.36% for manually written Devanagari characters. Deshpande et al. [19] utilized a similar chain code highlights with a customary articulation to create an encoded string from characters and improved the acknowledgment precision by 1.74%. A two-phase arrangement approach for transcribed characters was accounted for by S. Arora [20] where she utilized basic properties of characters like shirorekha and spine in the principal stage and in another stage utilized crossing point highlights. These highlights additionally took care of into a neural organization for the order. She additionally characterized a technique for finding the shirorekha appropriately. This methodology has been tried on 50,000 examples and gotten 89.12% exactness. In [21], S. Arora consolidated various highlights, for example, chain codes, four side perspectives, and shadow based highlights. These highlights were taken care of into a multilayer perceptron neural organization to perceive 1500 manually written Devanagari characters and get 89.58% precision.

A fluffy model-based acknowledgment approach has announced by M. Hanmandlu [22]. The highlights are removed by the case approach which separated the character into 24 cells (6×4 framework), and a standardized vector separation for each crate was registered aside



from the unfilled cells. A reuse strategy is additionally used to improve the speed of the learning of 4750 examples and acquired 90.65% exactness. The work introduced in [23] registered shadow highlights, chain code highlights and ordered the 7154 examples utilizing two multilayer perceptrons and a base alter separation technique for manually written Devanagari characters. They detailed 90.74% precision. Kumar [24] has tried five distinct highlights named Kirsch directional edges, chain code, directional separation appropriation, slope, and separation change on the 25,000 transcribed Devanagari characters and revealed 94.1% exactness. During the test, he found the inclination highlight beat the staying four highlights with the SVM classifier, and the Kirsch directional edges include was the most fragile entertainer. Another sort of highlight was likewise made that processed all out separation in four ways in the wake of figuring the inclination guide and neighborhood pixels' weight from the double picture of the example. In the paper [25], Pal applied the mean channel multiple times before extricating the course inclination includes that have been diminished utilizing the Gaussian channel. They utilized altered quadratic classifier on 36,172 examples and announced 94.24% precision utilizing cross-approval strategy. Buddy [26] has additionally expanded his work with SVM and MIL classifier on a similar information base and got 95.13% and 95.19% acknowledgment precision individually.

Regardless of the higher acknowledgment rate accomplished by existing techniques, there is still opportunity to get better of the transcribed Devanagari character acknowledgment.

Devanagari transcribed character acknowledgment has been explored by various element extraction strategies and various classifiers. Scientists have utilized basic, measurable and topological highlights. Neural organizations, KNN (K-closest neighbors), and SVM (Support vector machine) are basically utilized for grouping. In any case, the main exploration work was distributed by I. K. Sethi and B. Chatterjee [17] in 1976. The writers perceived the transcribed Devanagari numerals by an organized methodology which found the presence and the places of even and vertical line fragments, D-bend, C-bend, left inclination and right inclination. A directional chain code based element extraction procedure was utilized by

2.1 Deep Convolutional Neural Networks (DCNN)

The profound convolutional neural organization can be comprehensively isolated into two significant parts as appeared in Figure 1, the initial segment contains the arrangement of option convolutional with max-pooling layers, and another part contains the grouping of completely associated layers. An article can be perceived by its highlights which are legitimately subject to the conveyances of shading force in the picture. The Gaussian, Gabor, and so forth channels are utilized to record these shading power circulations. The estimations of a portion for these channels are predefined, and they record just the particular appropriation of shading power. The piece esteems won't change according to the reaction of the applied model. Be that as it may, in DCNN, the estimations of the portion are being refreshed by the reaction of the model. That assists with finding the best part esteems for the model. The option convolutional and max-pooling layers carry out this responsibility impeccably. Another piece of DCNN is completely associated layers which contain various neurons, similar to the basic neural organization in each layer that gets a significant level component from the past convolutional-pooling layer and registers the loads to order the item appropriately.

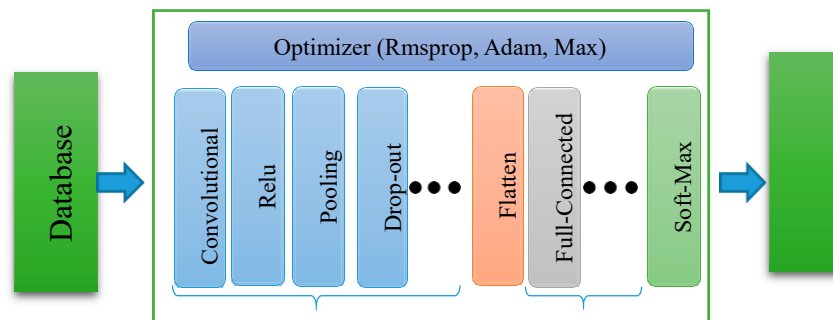


Figure 1. The schematic diagram of deep convolutional neural network (DCNN) architecture.

3. Research Method

3.1 Experiment

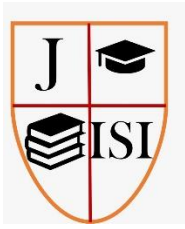
Tests were done on two information bases: ISIDCHAR and V2DMDCHAR utilizing the DCNN, layer-wise DCNN and diverse versatile inclination strategies. As it is difficult to portray the quantity of layers of DCNN that can deliver the best outcome, we thought about six diverse organization designs (NA) of DCNN as appeared in Table 1. NA-1 contains just single convolutional-pooling layer and 500 completely associated neurons to watch the principal reaction of DCNN. The following, NA-2 has twofold the quantity of completely associated neurons. The point is to watch the effect of upgrade. Further, NA-3 and NA-4 have two C-P layers with variety in the quantity of parts to examination the effect of two C-P layers. The last, NA-5 and NA-6 have three C-P layers.

At first, the distinctive organization structures of DCNN were applied on every information base to discover the best model for that specific information base and afterward the proposed layer-wise DCNN was applied to watch the effect of that model. The models have likewise been tried with various versatile slope techniques to these strategies; they are additionally under trial to watch their exhibition. Our work additionally shows the effect of various versatile angle techniques on acknowledgment exactness.

Table 1. Various network architectures of deep convolutional neural network used.

Network	Model Architectures
NA-1	64IN64-64C2-Relu-4P2-500FC-47OU
NA-2	64IN64-64C2-Relu-4P2-1000FC-47OU
NA-3	64IN64-32C2-Relu-4P2-32C2-Relu-4P2-1000FC-47OU
NA-4	64IN64-64C2-Relu-4P2-64C2-Relu-4P2-1000FC-47OU
NA-5	64IN64-32C2-Relu-4P2-32C2-Relu-4P2-32C2-Relu-4P2-1000FC-47OU
NA-6	64IN64-64C2-Relu-4P2-64C2-Relu-4P2-64C2-Relu-4P2-1000FC-47OU

The trials were totally executed on the ParamShavak supercomputer framework having two multicore CPUs with every CPU comprising of 12 centers alongside two quickening agent cards. This framework has 64 GB RAM with CentOS 6.5 working framework. The profound neural organization model was coded in Python utilizing Keras—a significant level neural organization API that utilizes Theano Python library. The fundamental pre-



handling undertakings like foundation end, dark standardization and picture resizing were done in Matlab. ISIDCHAR and V2DMDCHAR information bases.

The ISIDCHAR [26] was set up by scientists of the Indian Statistical Institute, Kolkata. They gathered the examples from people of various age gatherings to oblige the most extreme variety of composed characters. Aside from that, the examples are additionally gathered from the filled activity structures and post-cards that makes this information base so practical. This information base comprises of 36,172 grayscale pictures of 47 distinctive Devanagari characters. Attributable to the collection of tests from numerous creators, this information base conveys an assortment of tests in each class, and the foundation of the examples is likewise exceptionally clueless. V2DMDCHAR [31] has been set up by Vikas J. Dongre and Vijay H. Mankar's in 2012. This information base has 20,305 examples of transcribed Devanagari characters.

3.2 Experimental Setup

The analyses were performed to examine the impacts of various organization models, analyzers, and layer-wise trainings. The main period of trials was performed to watch the best organization design for the information base, and afterward the best-watched network engineering was tried with six distinctive analyzers to locate the best streamlining agent. A sum of 12 (6 + 6) unique trials were performed on the information base. The second period of examinations intended to watch the impact of layer-wise preparing. The layer-wise preparing was just performed with the best organization design and best streamlining agent chose in the main stage.

Each enhancer had its own arrangement of boundaries. In our trials, the analyzer boundaries were kept according to their default esteems or as proposed by the creator. The amended direct initiation work was utilized for whole examinations to alleviate the angle disappearing issue. The entirety of squares of the distinction among target and watched values was determined to assess the loss of the profound organization. Each organization was prepared for 100 ages utilizing smaller than normal bunches of size 200.

4. Findings and Discussions

The main period of examinations was performed on ISIDCHAR to analyze the best profound organization engineering. We recorded the acknowledgment precision at various organization design utilizing the Adam streamlining agent during every one of the 50 ages. The outcomes as far as the most extreme, least, mean, and standard deviation estimations of acknowledgment exactness are accounted for in Table 2.

The best acknowledgment exactness was gotten with the organization engineering NA-6, and the least acknowledgment precision was acquired with the organization design NA-1. Figure 3 shows the acquired acknowledgment exactness at every age. The organization NA-1 created 85% acknowledgment exactness since it has only one convolutional layer. The organization NA-3 and NA-5 delivered higher acknowledgment correctnesses of 91.53% and 93.24% individually in light of the fact that these organizations have a more convolutional layer. This improvement means that the augmentation of the convolutional layer in profound convolutional neural organization created best outcomes. In our trials, we watched the improvement in the acknowledgment

Precision by expanding the quantity of parts of convolutional layer. The organization

models NA-2, NA-4 and NA-6 had a larger number of pieces than NA-1, NA-3 and NA-5 and they created higher acknowledgment exactness as seen in Table 2. The quantity of teachable boundaries for each organization engineering is appeared in Table 3. The whole organization design was likewise tried utilizing the RMSProp enhancer, and the outcomes have revealed in Table 4. The NA-6 organization delivered 96.02% acknowledgment exactness with RMSProp while 95.58% with Adam. The conduct of NA-6 with RMSProp at every age can be found in Figure 4.

Accuracy by increasing the number of kernels of convolutional layer. The network architectures NA-2, NA-4 and NA-6 had more kernels than NA-1, NA-3 and NA-5 and they produced higher recognition accuracy as observed in Table 2. The number of trainable parameters for each network architecture is shown in Table 3. The entire network architecture was also tested using the RMSProp optimizer, and the results have reported in Table 4. The NA-6 network produced 96.02% recognition accuracy with RMSProp while 95.58% with Adam. The behavior of NA-6 with RMSProp at each epoch can be seen in Figure 4.

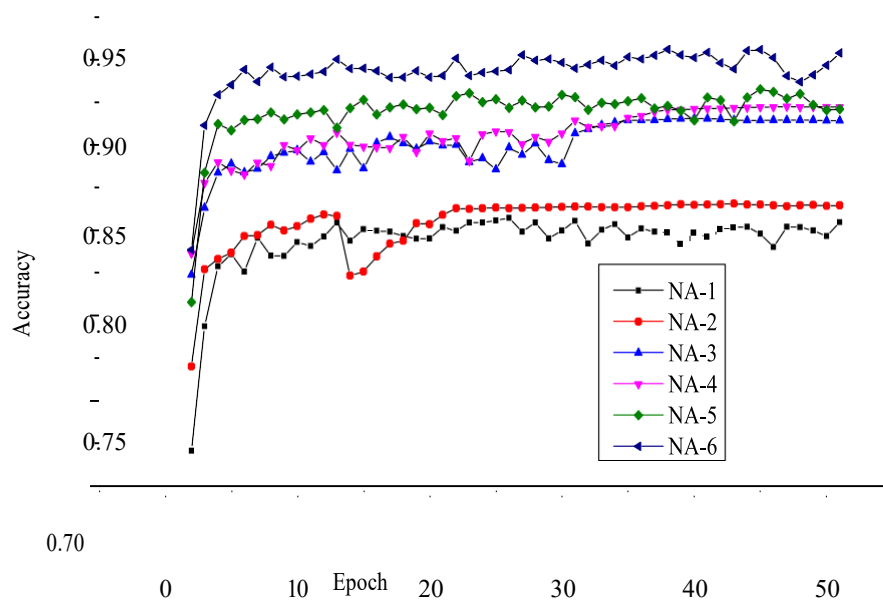
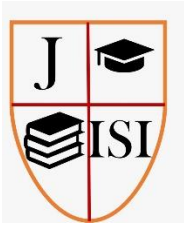


Figure 3. In this figure, we draw the recognition accuracy obtained with different network architectures on ISIDCHAR database at each epoch. The Adam optimizer was used.

Table 2. In this table, we report the results in term of maximum, minimum, mean, and standard deviation recognition accuracy obtained with different network architectures on ISIDCHAR when the system trained for 50 epochs with the Adam optimizer. The best scores are in bold.

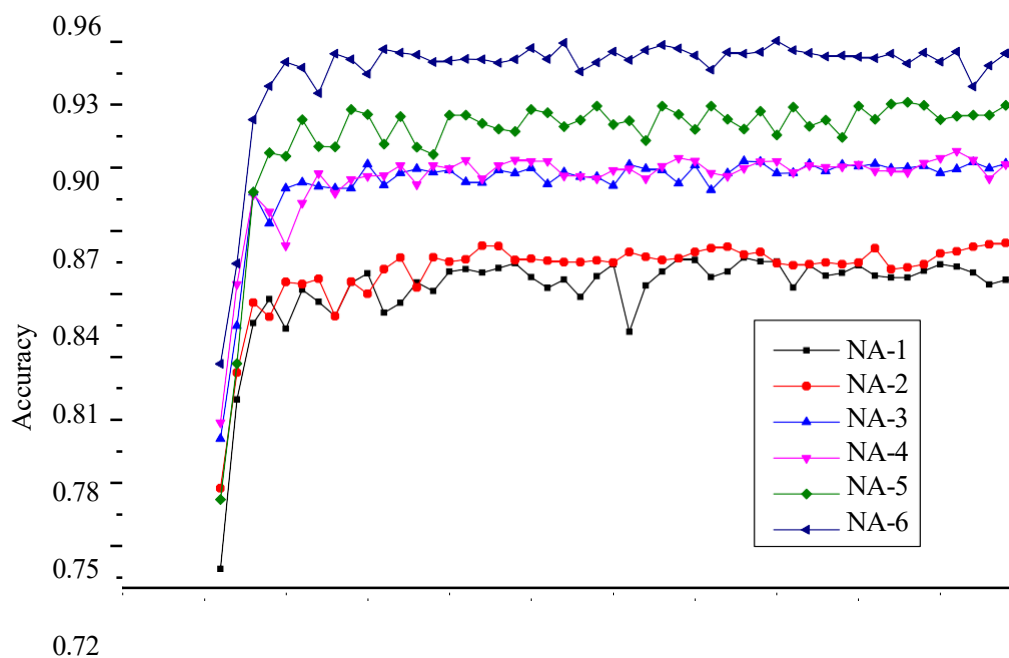


Recognition Accuracy	Different Network Architectures					
	NA-1	NA-2	NA-3	NA-4	NA-5	NA-6
Maximum	0.8571	0.8654	0.9153	0.9224	0.9324	0.9558
Minimum	0.7208	0.7701	0.8237	0.8363	0.8077	0.8385
Average	0.8436	0.8549	0.9000	0.9058	0.9190	0.9427
Std. Deviation	0.0204	0.0169	0.0165	0.0158	0.0178	0.0168

Network Architectures	Layer Type	Layer Size	Trainable Parameters	Total Parameters
NA-4	Conv1 layer	$64 \times 64 \times 64$	1088	14,514,735
	Conv2 layer	$64 \times 33 \times 33$	65,600	
	Dense layer	1000	14,401,000	
	Output layer	47	47,047	
NA-5	Conv1 layer	$32 \times 64 \times 64$	544	1,649,423
	Conv2 layer	$32 \times 33 \times 33$	16,416	
	Conv3 layer	$32 \times 17 \times 17$	16,416	
	Dense layer	1000	1,569,000	
	Output layer	47	47,047	
NA-6	Conv1 layer	$64 \times 64 \times 64$	1088	3,316,335
	Conv2 layer	$64 \times 33 \times 33$	65,600	
	Conv3 layer	$64 \times 17 \times 17$	65,600	
	Dense layer	1000	3,137,000	
	Output layer	47	47,047	

Table 4. In this table, we report the outcomes in term of most extreme, least, mean, and standard deviation acknowledgment exactness got with various organization structures on ISIDCHAR when the framework prepared for 50 ages with the RMSProp streamlining agent. The best scores are in intense.

Recognition Accuracy	Different Network Architectures					
	NA-1	NA-2	NA-3	NA-4	NA-5	NA-6
Maximum	0.8572	0.8641	0.903	0.9079	0.9311	0.9602
Minimum	0.7093	0.7475	0.7711	0.7788	0.7422	0.8067
Average	0.8383	0.8501	0.8927	0.8941	0.9150	0.9463
Std. Deviation	0.0321	0.0232	0.0210	0.0197	0.0308	0.0252



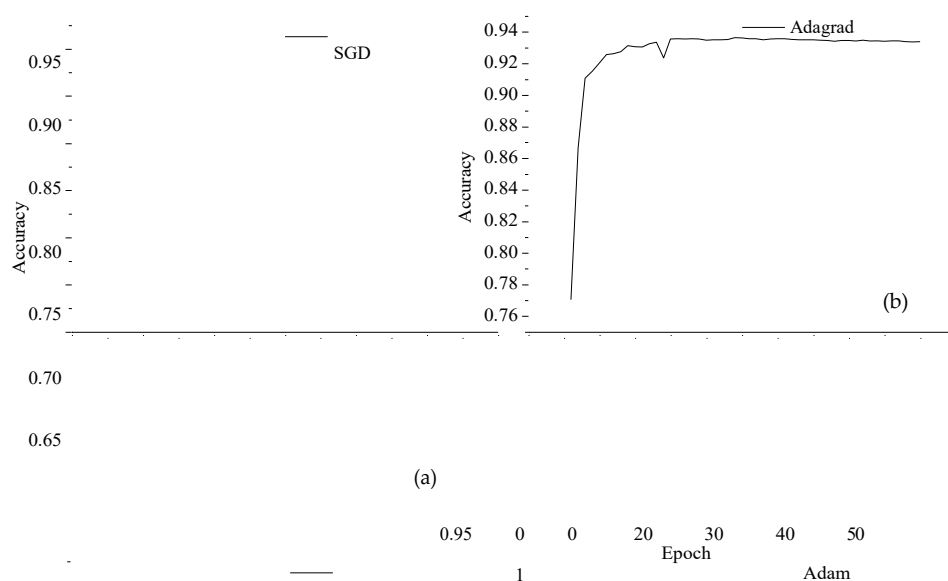
0 10 Epoch 20 30 40 50

Figure 4. In this figure, we draw the recognition accuracy obtained with different network architectures on the ISIDCHAR database at each epoch. The RMSProp optimizer was used.

The best acknowledgment precision of the ISIDCHAR information base was gotten with NA-6 organization engineering with RMSProp analyzer. Nonetheless, it might be conceivable that this organization could perform better with different streamlining agents. To additionally research, we performed explores different avenues regarding six diverse analyzers. Table 5 shows the acknowledgment precision got with NA-6 at various analyzers. The most elevated acknowledgment exactness 96.02% was recorded with NA-6 at RMSProp streamlining agent. The Adam streamlining agent beat the SGD and Adagrad enhancers. The AdaDelta, AdaMax, and RMSProp streamlining agents outflanked the Adam analyzer. Figure 5 shows the exhibition of individual enhancer.

Table 5. In this table, we report the outcomes in term of greatest, least, mean, and standard deviation acknowledgment exactness got with NA-6 on ISIDCHAR when the framework prepared for 50 ages with the diverse analyzers. The best scores are in intense.

Recognition Accuracy	Different Optimizers					
	SGD	Adagrad	Adam	AdaDelta	AdaMax	RMSProp
Maximum	0.931	0.9364	0.9558	0.9565	0.9579	0.9602
Minimum	0.6933	0.7703	0.7585	0.7605	0.7851	0.8067
Mean	0.9168	0.9280	0.9411	0.9457	0.9448	0.9463
Std. Deviation	0.0365	0.0252	0.0274	0.0311	0.0256	0.0252



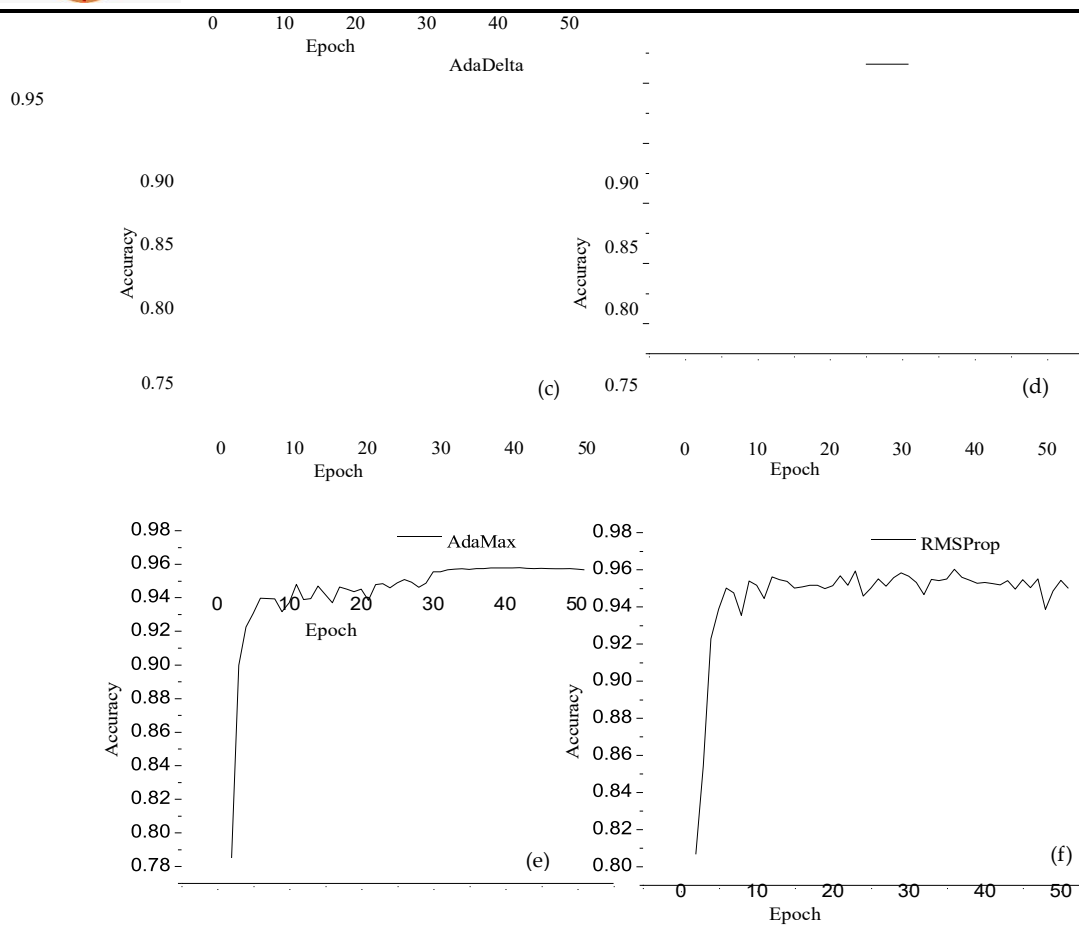


Figure 5. In this figure, we draw the acknowledgment precision acquired with NA-6 organization engineering at various streamlining agents (a) SGD; (b) Adagrad; (c) Adam; (d) AdaDelta; (e) AdaMax; (f) RMSProp; on the ISIDCHAR information base at every age.

We found that the NA-6 organization design with RMSProp analyzer delivered the most noteworthy acknowledgment exactness. This organization was again prepared by layer-wise model as depicted in Section 3.3. This organization was tried with ISIDCHAR, V2DMDCHAR, and consolidated information bases. The outcomes are accounted for in Table 6. It has been seen that a decent upgrade in the acknowledgment precision was recorded by the layer-wise preparing model. The 97.30% acknowledgment precision was gotten on ISIDCHAR information base and 97.65% acknowledgment exactness acquired on V2DMDCHAR information base. The layer-wise preparing model was likewise applied subsequent to joining both the information bases and acquired 98% acknowledgment precision when 70% of the examples were utilized for preparing and the rest utilized for testing. The current work is contrasted with past takes a shot at ISIDCHAR information base in Table 7.

Table 6. In this table, we revealed the greatest acknowledgment exactness acquired with NA-6 and RMSProp analyzer on ISIDCHAR, V2DMDCHAR and consolidated both when the model was prepared layer-wise.

Database	No. of Samples	Recognition Accuracy	
		DCNN	Layer-Wise DCNN
ISIDCHAR	36,172	96.02%	97.30%
V2DMDCHAR	20,305	96.45%	97.65%
ISIDCHAR+V2DMDCHAR	56,477	96.53%	98.00%

Table 7. Comparison of recognition accuracy by other researchers.

S. No.	Accuracy Obtained	Feature; Classifier	Method Proposed by	Data Size
1	95.19	Gradient; MIL	U. Pal [26]	36,172
2	95.24	GLAC; SVM	M. Jangid [32]	36,172
3	96.58	Masking; SVM	M. Jangid [33]	36,172
4	96.45	DCNN	Proposed work	36,172
5	97.65	SL-DCNN	Proposed work	36,172
6	98	SL-DCNN	Proposed work	56,477

5. Conclusion

Profound learning is one of the noticeable advances that have been tentatively concentrated with whole significant regions of PC vision and archive examination. In this paper, we tentatively built up a profound convolutional neural organization (DCNN) and versatile slope strategies to perceive the unconstrained manually written Devanagari characters. The profound convolutional neural organization helped us to locate the best highlights naturally and furthermore arrange them. We explored different avenues

regarding a transcribed Devanagari character information base with six distinctive DCNN network designs just as six diverse streamlining agents. The most noteworthy acknowledgment precision 96.02% was gotten utilizing NA-6 organization design and RMSProp—a versatile angle strategy (enhancer). Further, we again prepared DCNN layer-wise, which is likewise received by numerous analysts to upgrade the acknowledgment precision, utilizing NA-6 organization engineering and the RMSProp versatile angle strategy. Utilizing DCNN layer-wise preparing model, our information base acquired 98% acknowledgment exactness, which is the most noteworthy acknowledgment precision of the data set.

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