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A Study of fixed-point theorem and related problems in Hilbert space

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ABSTRACT

Scribbling on the spot, known as charm tracing via hand movements in a 3D free space, is the way forward for marginal autonomous, simulated interface communication. Although the recognition of sole instroke character is very easy, continuous writing recognition is difficult because there are no boundaries between letterings. Wandering hand movement while writing adds racket to the input, making it problematic to accurately recognise. The secret to accurate identification of written air typescripts is the absence of noise and the segmentation of the character of nonstop writing. We present a glitching window approach that isolates a small piece of the spatially-temporal input for noise deletion and digital segmentation from the air writing operation. Recent Neural Networks (NNNs) have great potential and are the foundation of our architecture when dealing with temporal data. We only use sequential co-ordinates to access our device from any generic camera as an input. We note a drop in accuracy due to the noise between digit transitions Our method, on the other hand, achieved accuracy of 98.45 percent for single numerals and 82.89 percent for multiple numerals under normal conditions.
Keywords: Air Writing · Gratitude of Manuscript · Human Processor Contact · Long Short-Term Memory · Recurring Neuronic System ·

1. INTRODUCTION

Recent fees in gesture gratitude and wave detection have paved the way for new directions in human-computer interaction. However, in some situations, these input options may not be accessible or appropriate. Gesture and wave following algorithms have simplified and advanced user interaction methods. However, these basic patterns are insufficient for detecting composite string input. Air-writing, also known as the writing of fonts in three-dimensional space with free hand gestures and six degrees of freedom. This presents its own collection of problems for character recognition, and becomes more difficult for a string of characters

However, these additional radars are costly and not included in the majority of common devices, making such systems inaccessible to the general public.

Furthermore, certain characters can be sub-shapes of others. So, it is difficult to tell if a character has been completed and the person who is using is able to go on to the forward character or whether the user is still tracing the character.

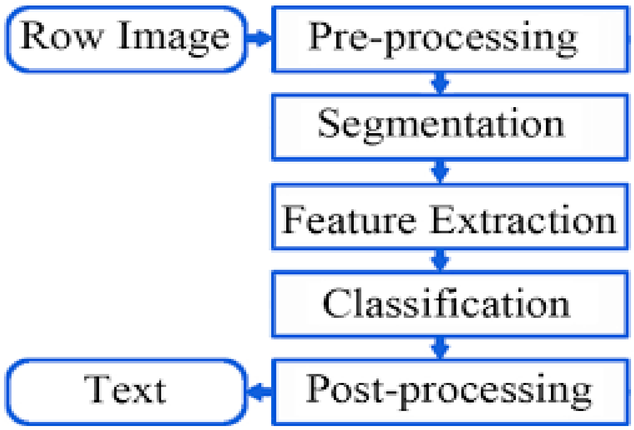

Fig 1: Stages Defined Above

Motivation

A person's handwriting is always different, much like our fingerprints, inspiring researchers with this novel approach to jobs in this challenging and demanding industry.Around the world, a variety of languages are spoken. Many languages have vanished due to little usage and the fact that they are found in rural or inaccessible areas of the world. As a result, using technology such as OCR and natural language processing to prevent language extinction is strongly suggested at this time. Only a few handwritten OCR systems are available for the world's over 7000 languages .Due to a lack of effort, most languages developed from the Indic script appear to be on the verge of extinction. As a result, character recognition research for Indian scripts is in high demand.

Main contributions of the article

- The most essential part of this paper is to describe work on the recognition of handwritten Indic scripts from earlier years (2000–2019) by examining more than 100 articles from reputable publications and notable conferences.
- It presents a comparison examination of our survey with other relevant surveys and review articles, as well as a complete explanation of the uniqueness and challenges of main Indic scripts.
- This paper examines a number of prestigious datasets for handwritten Indic script recognition research.
- This paper analyses a variety and classification techniques of handwritten Indian character acknowledgement in detail.
- Finally, a framework is developed with the goal of overcoming the shortcomings of existing categorization methods. As shown in Algorithm1, an enhanced PSO algorithm for automatically constructing optimal CNN architecture has been proposed.

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Outline of the article

The final portion compares the current survey with traditional comparable surveys and reviews. The survey technique that comprises a design, study questionnaire, sources of information, search criteria, and other features to help researchers carry out the survey is explained in Section 4. Section 5 presents a thorough review for several Indian scripts of Standardized data sets. The three basic classification methodologies are neural network-based approaches, SVM-based techniques and different techniques. Section 7 summarises the investigation based on the findings and associated research. Section 8 discusses the difficulties in recognising characters in Indian script and discusses future study opportunities.

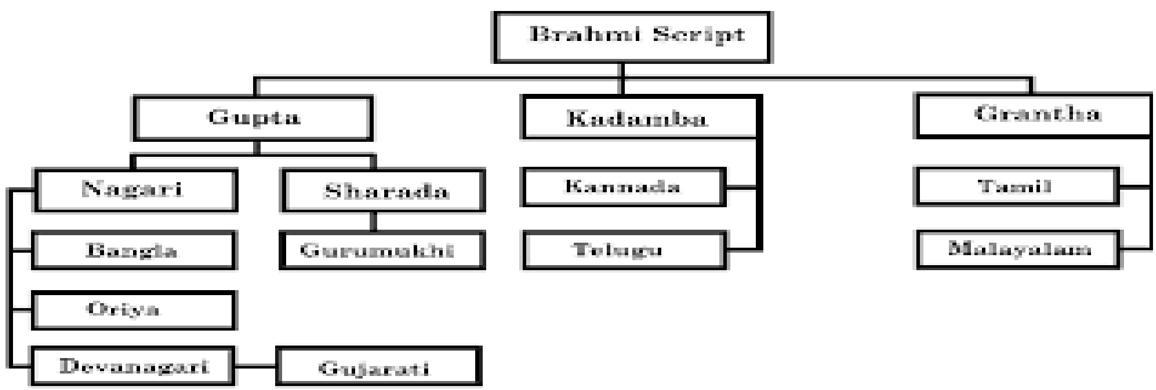

Fig 2: Generation of Indic scripts

2. RELATED SURVEY

Since handwriting research on the identification of script character still in its early stages, the analysis and combination of past findings is necessary through a rigorous up-to-date review. Table 2 summarises our survey's comparison to other relevant surveys and review papers.

3. SURVEY PORTAL

3.1. Planning the survey

The first step in conducting a systematic survey is to determine why you want to research handwritten OCR for Indian scripts. The survey constructs a survey programme, analyses research reports from several online libraries, provides survey findings and ultimately identifies research issues and future orders, all of which are stages of this survey.

3.3 Information Sources

The study takes into account research papers. Aside from this, numerous books, theses, and other internet sources and materials are also employed to conduct a more extensive and comprehensive survey. Table 4 summarises these sources of knowledge.

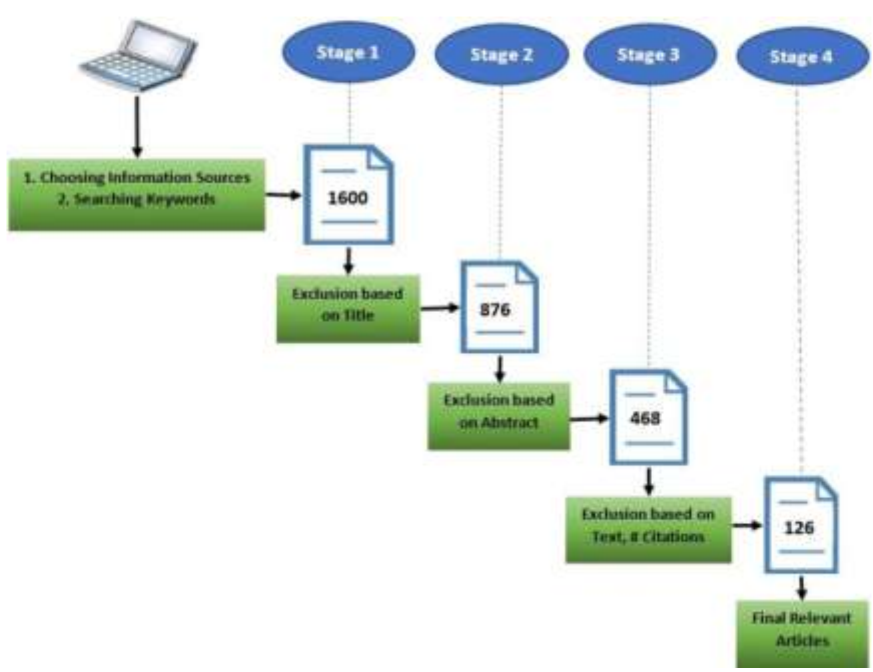

Fig 4:Demonstration of search criteria

3.4. Search Criteria

The selection of articles linked to character recognition is the first step in the search criteria. The research articles are categorised based on the year they were published, the dataset they used, the feature extraction techniques they used, and the classifiers they used. For the initial selection, several keywords are utilised. After doing some research on the internet, I was able to find around 1600 articles. The papers are then further refined by being removed based on their title, abstract, and amount of citations.

3.5. Data Extraction

The data extraction phase is built on top of the quality evaluation process. The criteria for data extraction illustrate how the study documents to be evaluated, comparing, analysed and interpreted can be used for collecting significant and relevant data items (AppendixB). Since it was difficult to extract all the data elements required from multiple investigations. Because of this problem, numerous authors have been contacted when necessary to get extra study information.

4. Suvey of Indic scriptsdatasets

In evaluating a new application model, the database is quite important. A lot of handwritten datasets for various Indic scripts have been developed in recent years. This section examines several benchmark and standardised datasets for Indian scripts in depth.

In addition to the datasets given above, the researchers have produced their own datasets.

The usage of standardised datasets is strongly. As a result, it's worth noting that successful research necessitates putting in extra work to create large, For every Indian script, stable datasets. The availability of standard data sets is shown for several Indian scripts in Figure 8, and an analysis has been conducted based on the sources utilised in this study.

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TABLE 5 : Detailed description for various scripts of standardised handwritten data sets.

“Dataset name (Reference)	Script	Dataset type	Dataset size
ISI-HDND [31]	Devanagari	Numerals	22,556
CMATERdb 3.2.1 [28]	Devanagari	Numerals	3000
HPL-iso-dev-char [32]	Devanagari	Characters	29,970
DHCD [33]	Devanagari	Characters	92,000
CMATERdb 2.2.3 [29]	Devanagari”	Words	15,528
“CMATERdb 1.4 [30]	Devanagari	Text lines	150 document images
CMATERdb 3.1.1 [34]	Bengali	Numerals	6000
ISI-HBND [39]	Bengali	Numerals	23,392
CMATERdb 3.1.2 [35]	Bengali	Basic characters	15,000
CMATERdb 3.1.3 [36]	Bengali	Compound characters	42,697
CMATERdb 3.1.4 [37]	Bengali	Modified characters	2044
CMATERdb 2.1.3 [29]	Bengali	Words	18,931
CMATERdb 1.1 [38]	Bengali	Text lines	100 document images
CMATERdb 3.4.1 [28]	Telugu	Numerals	6000
HPL-iso-telugu-char [40]	Telugu	Characters	45,154
HPL-iso-tamil-char [41]	Tamil	Characters	82,000
KHTD [42]	Kannada	Text lines and words	4298 text-lines, 26,115 words
ISI-HOND [39]	Oriya	Numerals	5970
IITBBS [43]	Oriya	Characters	35,000”

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5. "State-of-the-art in handwritten Indic scriptsOCR

Based on their evolution and similarities, the Indic scripts are divided into three basic divisions or groups in this work."

• The first group is the Devanagari, Gurumukhi and Bengali script, as each character has a shirorekha or matra. Because the character sets of Kannada and Telugu are so close, the second category is made up of these two scripts. By 1500 AD, various modifications had transformed the ancient Kannada script into Telugu and Kannada scripts. Gujarati, Oriya, Tamil, and Malay- alam scripts make up the third category.

5.1. "Reported work on Devanagari, Gurumukhi and Bengaliscripts

5.1.1 Feature Extraction"

The functional extraction process reduces a large, redundant set of parameters to a smaller set of parameters known as a vector. Feature vectors are important because they efficiently and unambiguously recognise patterns, improving the OCR recognition rate [44,45]. Statistical and structural features are the two types of features that are commonly used.

- **Statistical Features**
- **Structural Features**

5.1.2. Classification and Recognition

Classification is a large research field in and of itself, as well as a crucial stage in character identification.

A. Neural Network basedtechniques

Techniques based on artificial neural networks (ANNs) could be utilised to classify and recognise handwritten characters [79,80]. ANN performs computations at a substantially higher frequency than traditional methodologies because to its parallel architecture. These classifiers are designed to resemble human brains.

The suggested model was assessed using the ISIDCHAR database of 56,477 handwritten samples of character, claiming a 98% identification accuracy. Examples are neural feed forward networks, neuronal feedback networks, self-organization neural networks and recurrent neural networks.

B. SVM based

SVM can solve a two-class or binary classification issue, and it can also solve a multi-class classification issue by combining numerous binary SVMs using multiple methods such as winner-takes-all, max-win approach, and so on.

Methodology	Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)
Kale et al. [55]	27,000	Legendre and Zernike moment	Support Vector Machine	98.51(Basic), 98.30(Compound)
Jangid and Srivastava [66]	56,477	Automatic	SL-DCNN	98.00
Singh and Maring [58]	20,000	Zone based centroid, CC, Distance Profile and BDD	Support Vector Machine	97.61
Shelke and Apte [59]	40,000	Pixel density features, Structural	Fuzzy system and FFNN	96.95
Yadav and Purwar [63]	4428	Histogram of oriented gradient, Projection Profile	Quadratic SVM	96.60
Jangid et al. [84]	36,172	Automatic	DCNN with RMS Prop	96.00
Pal et al. [67]	36,172	Curvature, Gradient	Mirror Image Learning	95.19(Curvature), 94.94(Gradient)
Sarkhel et al. [89]	22,086	Multiscale-multicolumn CNN	Support Vector Machine	95.18
Singh et al. [54]	31,860	Curvelet based features	K-Nearest Neighbour	93.80
Singh and Lehri [68]	1000	Pixel based features	Backpropagation NN	93.00
Arora et al. [51]	4900	Shadow, CC histogram, Intersection features and Line fitting	Feed-foward NN	92.80
Narang et al. [87]	5484	SIFT, Gabor filter, PCA	Poly-SVM	91.39
Sharma et al. [50]	11,270	Direction CC histogram”	Modified QDF	80.36

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Surinta et al. [60] suggested a 10-fold cross-validation RBF kernel based SVM classifier for recognising handwritten Bengali fundamental letters.

5.2.ReportedworkonGujarati,Oriya,TamilandMalayalamscripts

5.2.1. Featureextraction

Pal et al. [117] employed a gradient-based approach using the Fisher ratio (F-ratio) to recognise handwritten Oriya characters. Initially, To construct a 400-dimensional gradient vector, Roberts and Gaussian filters are utilised. Then an F-ratio-based method of weighting the feature vector was changed. By decreasing the characteristics of the same sections of the similar characteristics and reinforcing characteristics of the characteristics of comparable characteristics this feature weighting methodology makes it much easier to identify similar shaped characters.

For handwritten Tamil writing, Bhattacharya et al. [121] Presented a method for two stage recognition.

Table 7

Accurate recognition of the handwritten characters of Devanagari.

Table 8

Accuracy of recognition of handwritten characters gurumukhi.

Methodology	Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)
Kumar and Gupta [64]	2700	Directional, LBP, Regional features	Deep Neural Network	99.30
Aggarwal and Singh [61]	7000	Curvature and Gradient	Support Vector Machine	98.56
Kumar et al. [56]	3500	Power curve fitting	K-Nearest Neighbour	98.10
Kumar et al. [62]	10,500	Discrete cosine transform	SVM with linear kernel	95.80
Sinha et al. [71]	7000	Zone based features	SVM, KNN	95.11, 90.64
Siddharth et al. [70]	7000	Zoning density and BDD	Support Vector Machine	95.04
Singh et al. [72]	7000	Gabor features	SVM with RBF Kernel	94.29
Jain and Sharma [69]	15,000	Automatic features	Neocognitron NN	92.78
Garg et al. [76]	8960	Peak extent,	Linear	92.30
Kaur	2450	MDP, PCA	SVM+polySVM+l	92.08

Table 9

Precise recognition of fundamental and compound Bengali handwriting characteristics.

Methodology	Dataset size	Dataset type	Feature extraction	Classification technique	Recognition accuracy (%)
Sarkhel et al. [89]	42,697	Compound	Multiscale-multicolumn CNN	Support Vector Machine	98.12
Keserwani et al. [85]	41,536	Compound	Automatic	Unified-CNN	98.12
Roy et al. [91]	42,959	Compound	Automatic	SL-DCNN	90.33
Pramanik and Bag [75]	10,240	Compound	Chain code histogram	Multi-layer perceptron	88.74
Bag et al. [57]	19,800	Compound	Topological	Template matching	86.74
Pal et al. [74]	20,543	Compound	Gradient	MQDF	85.90
Das et al. [53]	19,765	Compound	Shadow, Quad tree, LR	Support Vector Machine	80.51
Keserwani et al. [85]	15,000	Basic	Automatic	Unified-CNN	98.56
Rabby et al. [65]	15,000	Basic	Automatic extraction	BornoNet"	98.00
Sarkhel et al. [73]	15,000	Basic	"CG based Quad tree LR, Convex hull	Support Vector Machine	87.28
Sarkhel et al. [92]	15,000	Basic	LR, Enhanced harmony search	SVM with RBF kernel	86.53
Roy et al. [93]	15,000	Basic	ABCO, Gradient features	Support Vector Machine	86.40
Gupta et al. [94]	15,000	Basic	HOG, Convex hull, LR, Harmony search	Support Vector Machine	86.10
Surinta et al. [60]	5527	Basic	Scale invariant feature transform	Support Vector Machine	85.00
Basu et al. [52]	10,800	Basic	Modified shadow, Octant centroid, LR"	MLP based two stage classifier	80.58

Table 10

"Recognition accuracies for handwritten Kannada script."

“Methodology	Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)
Karthik et al. [104]	18,800	Distributed average of gradients	Deep belief networks	97.04
Dhandra and Mukarambi [101]	1400	Normalized chain code and wavelet decomposition	K-Nearest Neighbour	95.07
Rajput and Horakeri [98]	6500	Fourier descriptors and chain codes	SVM	93.92
Rani et al. [105]	5200	Automatic	Alex net	92.00
Pasha and Padma [106]	4800	Structural features and Wavelet transform	ANN	91.00
Pal et al. [95]	10,779	Directional features	Quadratic classifier	90.34
Dhandra et al. [97]	1400	Spatial features	K-Nearest Neighbour	90.10
Angadi and Angadi [107]	2490	Structural features	SVM	89.84
Vaidya and Bombade [100]	7350	Positional features	GRNN	85.62
Sangame et al. [96]	1625	Moment invariant features	K-Nearest Neighbour	85.53
Mukarambi et al. [99]	2800	Zone based and pixel density features”	SVM	73.33

Table 11

Precise handwritten Telugu script accuracy recognition.

“Methodology	Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)”
Sarkhel et al. [89]	45,217	MMCNN	SVM	95.76
Sastry et al. [108]	Not-specified	3D features	Decision Tree	93.10
Angadi et al. [111]	45,133	Automatic	CNN with SGD optimizer	92.40
Pal et al. [95]	10,872	Directional	Quadratic classifier	90.90
Lakshmi [103]	18,000	Block wise pixel	KNN and SVM	90.80

		count		
Manisha et al. [109]	23,875	Hybrid and zone based features	KNN	88.15
Sastry et al. [102]	19,250	Zoning method	Nearest Neighbour classifier	78.00

Table 12
"Recognition accuracies for handwritten Gujarati script."

"Methodology	Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)
Sharma et al. [139]	20,500	Structural decomposition	Polynomial kernel SVM	99.48
Pareek et al. [140]	10,000	Automatic	CNN with Adam optimizer	97.21
Thaker and Kumbharana [116]	750	Closedloops,CDC and End points	Decision tree classifier	88.78
Prasad and Kulkarni [115]	16,560	GPXNP	Weighted KNN	86.33
Prasad et al. [112]	Unspec ified	Structural features	Template matching	71.66
Prasad and Kulkarni [114]	16,560	GPXNP	Adaptive NFC using feature selection	68.67
Patel and Desai [113]	Unspec ified	Centroidandmoment based features	Tree classifier and KNN"	63.10

Table 13
Accuracy of handwritten Oriya script recognition.

"Methodology	Dataset size	Feature extraction	Classification technique	Recog nition accura cy (%)
Sethy et al. [120]	9400	Zone based mean angular values and mean ED	Quadratic discriminant classifier	97.40
Wakabayashi et al. [134]	18,190	Gradient and F-ratio	Modified QDF	95.14
Dash et al. [119]	7800	Binary ESAC	K-Nearest Neighbour"	95.01
"Pal et al. [117]	18,190	Gradient, Curvature and PCA	Quadratic classifier	94.60

Padhi [118]	Not specified	Average angle, distance and SD	Average	BPNN and Genetic Algorithm	94.00
Dash et al. [141]"	10,200	Tetrolet+ SCC		Nearest Neighbour	93.24

Table 14
Accuracy of handwritten Malayalam script recognition.

Methodology	"Dataset size	Feature extraction	Classification technique	Recognition accuracy (%)
Raju et al. [132]	19,800	Gradient based features, run length count	Simplified quadratic discriminant function and MLP	99.78(MLP), 99.66(SQDF)
Jomy et al. [131]	13,200	Gradient, Curvature and PCA	SVM with RBF kernel	97.96
Jino et al. [135]	18,000	Automatic features	Stacked Long Short Term Memory	97.00
Manuel et al. [136]	2120	Curvelet transform	Multi-layer perceptron	95.99
Chacko et al. [130]	9000	Wavelet Energy features	Extreme Learning Machine	95.59
Moni and Raju [129]	19,800	Directional features	Modified QDF	95.42
Kishna et al. [143]	Unspecified	Texture features	Hybrid HMM with ANN	93.40
Manjusha et al. [133]	29,302	Reduced scattering convolutional network"	Linear SVM	91.05

6. CHALLENGES AND FUTURE PERSPECTIVES:

Several academics' efforts to recognise handwritten Indian scripts are depicted in the research papers reviewed in this survey.

- ***Resolutionofconfusingandsimilarcharacters*:** Certain characters are remarkably similar in Indian scripts, making it difficult and difficult to recognise the related characters. If the personal feature has been lost during the preprocessing stage or the distinguishing element is too little to detect because of differences in written styles, then it becomes more difficult to separate these comparable form characteristics. In order to be accurately recognised, certain characters demand particular attention.

- ***DevelopmentofOCRforhistoricalanddegradeddocuments*:**The amount of work done on degraded documents of poor quality is almost non-existent. As a result, studies in this approach should be conducted in order to advance study on deteriorated, noisy, and historical records. Several memory organisations will benefit from the acknowledgment of these deteriorated historical and ancient archives, which will aid in the digitization of their manuscript collections. As a result, it will be highly valuable to philologists and historians in contributing to the preservation and advancement of historic legacy.

- ***Combination of multiple classifiers*:** Future research should focus on merging various classifiers to get an optimum combination in order to considerably increase classification performance. The sequential fusion method is typically used to handle big categories, whereas the parallel fusion method is utilised to improve the accuracy of the classifier.

7. PROPOSED FRAMEWORK

In this document, we have therefore focused our efforts upon offering a hybrid methodology to categorise that exceeds the most technological advanced methods. Deep neural networks (DNNs) showed that the recognition of difficult handwritten Indian scripts is superior to traditional machine learning technologies. The creation of a successful DNN from the ground up requires a considerable degree of field expertise.

7.1. Evaluate the fitness

Algorithm 1 Procedure PSO-CNN

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1: **Input:** The swarm or population size (N), training data (D_{train}), the number (e_{train}) of training epochs, maximum number of iterations (max)

2: **Output:** The optimal CNN architecture

3:X=X_1, X_2, ...,X_N *//InitializepopulationwitheachparticlecorrespondingtorandomCNNarchitecture*

4: **for** k = 1 to N **do**

5: p-best$_k$ X_k *//Initialize the personalbest*

6: X_k_loss, p-best$_k$_loss = L(X_k, D_{train},e_{train}) *//Evaluate thefitness*

7: **end for**

8: g-best=X_k*forallparticlesm,kmand*L(X_k,D_{train},e_{train})<L(X_m,D_{train},e_{train})

9: g-best_loss = X_k_loss

10: **for** iter = 1 to max **do**

11: **for** k = 1 to N **do**

12: X_k_velocity = Update_Velocity(X_k,ω)

13: X_k=Update_Particle(X_k)

14: X_k_loss = L(X_k,D_{train},e_{train}) *// Evaluate thefitness*

15: **if** X_k_loss<p-best$_k$_loss**then**

16: p-best$_k$$X_k$

17: p-best$_k$_loss =X_k_loss

18: **if** p-best$_k$_loss<g-best_loss**then**

19: g-best =X_k

20: g-best_loss =X_k_loss

21: **endif**

22: **endif**

23: **endfor**

24: **end for**

25: returng-best *//G-best will return the optimal CNNarchitecture*

8. UNTRIED ANALYSIS

The following subsections outline the yardstick data sets used to examine the model's performance. The experimental configuration and overall performance are then represented and carefully reviewed. Finally, the selected peer rivals are assessed by employing these state-of-the-art approaches.

8.1. Benchmark Datasets

To assess the effectiveness of the proposed approach, computational tests are carried out on two standard picture classification datasets. "CMATERdb 3.1.2 [35] and CMATERdb 3.1.3 [36], which are briefly mentioned in Section5.2," were utilised as benchmark datasets. The handwritten character dataset's 3-channel RGB images are then binarized, reducing the number of parameters in the suggested design.

9. Conclusion

The proposed technique is language-independent, despite the fact that the quizzes are conducted on English language numerals. Language models were avoided in order to make the system uniformly available. The urgency scheme suggested in our methodology prevents recognising any undesirable digit in a instroke motion. The proposed organization achieved an accuracy of 97.45 percent for single-digit numeral recognition and 81.89 percent for multi-digit numeral recognition. The work Kinect or LEAP wave, making it extremely usable. By studying the sub-strokes involved in tracing digits, we are currently working on improving the precision
.

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