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ORIGINAL RESEARCH ARTICLE

Linear discriminant analysis-based deep learning algorithms for numerical character handwriting recognition

Hayder M. A. Ghanimi[1,2], N. Alagusundari[3], Jainabbi Banda[4], Sudhakar Sengan[5,*], J. Somasekar[6], J. Thomas[7], Pankaj Dadheech[8]

[1] *Information Technology Department, College of Science, University of Warith Al-Anbiyaa, Karbala 56003, Iraq*

[2] *Department of Computer Science, College of Computer Science and Information Technology, University of Kerbala, Karbala 56001, Iraq*

[3] *Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu 641022, India*

[4] *School of Computer Science and Engineering-VIT, Andhra Pradesh 517501, India*

[5] *Department of Computer Science and Engineering, PSN College of Engineering and Technology, Tirunelveli 627152, India*

[6] *Department of Computer Science and Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bengaluru 560069, Karnataka, India*

[7] *Department of Science and Humanities, V. S. B. College of Engineering Technical Campus, Coimbatore 642109, Tamil Nadu, India*

[8] *Department of Computer Science and Engineering, Swami Keshvanand Institute of Technology, Management & Gramothan (SKIT), Rajasthan 302017, India*

*** Corresponding author:** Sudhakar Sengan, sudhasengan@gmail.com

ABSTRACT

Information processing requires handwritten digit recognition, but methods of writing and image defects like brightness changes, blurring, and noise make image recognition challenging. This paper presents a strategy for categorizing offline handwritten digits in both Devanagari script and Roman script (English numbers) using Deep Learning (DL) algorithms, a branch of Machine Learning (ML) that uses Neural Networks (NN) with multiple layers to acquire hierarchical representations of input autonomously. The research study develops classification algorithms for recognising handwritten digits in numerical characters (0–9), analyzing classifier combination approaches, and determining their accuracy. The study aims to optimize recognition results when working with multiple scripts simultaneously. It proposes a simple profiling technique, Linear Discriminant Analysis (LDA) implementation, and a NN structure for numerical character classification. However, testing shows inconsistent outcomes from the LDA classifier. The approach, which combines profile-based Feature Extraction (FE) with advanced classification algorithms, can significantly improve the field of HWR numerical characters, as evidenced by the diverse outcomes it produces. The model performed 98.98% on the MNIST dataset. In the CPAR database, we completed a cross-dataset evaluation with 98.19% accuracy.

Keywords: handwriting recognition; deep learning; neural network; feature extraction; linear discriminant analysis; accuracy

1. Introduction

This research explores handwritten digit recognition, a method that classifies human handwritten digits into 10 predefined classes (0–9). The model compares accuracy, errors, and testing-training time using a Support Vector Machine (SVM), Multilayer Perceptron, and Convolutional Neural Network (CNN) systems[1–5]. Handwritten digit recognition is crucial for number plate recognition, postal mail sorting, and bank cheque

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processing. Identifying handwritten digits in various scripts, mainly English and Devanagari, remains challenging despite digitisation. Electronic systems struggle to recognize Devanagari numbers, which are integral to the Hindi language. The intricate curves and lines of the Devanagari script require specialized solutions. Scientists have explored various algorithms and methodologies for a reliable and efficient HWR system[6–10]. Dual-script identification systems are essential in India due to the diverse linguistic landscape. Handwriting Recognition (HWR) numerical characters are crucial in multiple domains, especially in office automation. However, the uniqueness of an individual's handwriting adds complexity to identification. HWR numerical character systems must analyze numerals' structure, topology, and statistical characteristics and accommodate the inherent variations in shape and size[11–15].

The public eagerly anticipates technology recognising handwritten digits accurately after 35 years of research. However, no system can achieve 100% accuracy due to human confusion and ambiguities. Modern technology combines computer algorithms and handwriting insights to improve literary cognition and numerical character value[16–20]. It uses multiple handwriting styles to impart Sanskrit and English digits without scripts. To achieve data transformation accuracy and effectiveness, an electronic identifying system must be interconnected with existing systems. Periodic learning is necessary for HWR. Inclusivity in the digital age requires technology that supports different human languages and writing procedures. With an accurate, responsive numerical character, the HWR system demonstrates technological advancement and humanity's unique qualities.

Optical Character Recognition (OCR) helps computers read numbers like humans. This technology has revolutionised textual interaction, making alphanumeric letters and numerical character values simpler to recognise. OCR is required to convert handwritten data into ASCII or other computer-readable formats[21–25]. With numbers, character sizes, and backgrounds, OCR challenges, particularly when text is positioned over complicated images. Pattern recognition—including OCR and handwritten character recognition—improves computer-human interaction. Novel handwriting input recognition and Deel Learning (DL) techniques employing Artificial Neural Networks (ANN) may solve this problem. OCR's NN incorporates Feature Extraction (FE) to bridge the gap between machine processing and human-like recognition, providing continuous human-computer interactions.

Motivation of study:

- The paper addresses the challenges of handwritten data recognition, including size, thickness, position, and orientation, in email, hand-fill forms, and online tablets.
- It proposes two pattern classification methods for 0–9.
- The paper also addresses the issues of digit similarity, handwriting styles, and individual diversity, which affect digit appearance and formation.

The article is organized as follows: The detailed overview of diverse handwriting is given in Section 1, the related works are discussed in Section 2, the proposed handwriting Recognition using NN is given in Section 3, the result and discussion are illustrated in Section 4, and the article is concluded in Section 5.

2. Related works

Experiments by Pawan and Bhanu[26] to recognise characters in 1959 proved revolutionary. Early sixties work used Eden's 1968 analysis-by-synthesis technique. Eden's research demonstrated that handwritten characters have a finite number of conceptual features, which all syntactic character recognition techniques accepted.

For the intent of recognising unstructured asynchronous handwritten texts, an integrated Hidden Markov Model (HMM) framework was suggested. Markov chains have been utilised to model the structural section of the optical model, and a multilayer perceptron has been employed to quantify the output probability[27–29].

For the task of recognising handwritten English characters, multilayered perceptrons have been applied. Perimeter tracing and their Fourier classifiers are used to FE from the data. A character's identity is determined by evaluating its form while contrasting the features that set each character distinct from others[28–30]. Additionally, a review was conducted to determine how many hidden layer nodes must be present in order to achieve a high level of performance in the backpropagation network. The successful recognition of handwritten English letters has been claimed to be 94%, and the sum of training time involved has been significantly less[31–33].

The authors demoralized three different types of features. These features are the quantity features, the moment features, and the descriptive component features. Devanagari numerals are organised according to their order of classification. They achieved an accuracy of 90.10% for handwritten Devanagari numerals, which was made possible by executing a multi-classifier connectionist framework that they proposed to improve recognition accuracy[34–38].

A method which involves the performance of an array of strokes is suggested in some studys[39–42] as a method of generating a handwritten Tamil letter. It was determined to use a structure-based or shape-based representation of a stroke, in which a stroke is shown as a string of shape features. Using this string representation, an unknown stroke was identified by comparing its characteristics to an array of strokes using a string-based comparison method that revealed versatility. All of the basic strokes were recognised, resulting in the recognition of a full letter[43–45].

The researchers investigated handwritten Hindi and English numerical values. A fuzzy model is developed employing logarithmic membership functions to signify numerical values. Fuzzy sets are normalized distances derived from Box approach features[46–50]. Entropy optimisation predicts two fundamental variables that impact the membership function. The recognition rate for Hindi digits is 95%, and for the English language, 98.4%[51–55].

Over the years, numerous LDA variants have been projected to enhance performance. The authors' regularised LDA (RLDA) addresses the problem with a regularised within-class scatter. The study presented 2D exponential discriminant analysis for small samples[56–60]. SDA uses unlabelled data to expand the training set. The researchers developed a total rank between-class scatter matrix to reduce over-reducing. The authors deployed a scatter matrix from a small neighbourhood as a regularisation term[61–65].

3. Proposed methodology

Currently, the biggest problem in computational linguistics is creating a reliable system that can HWR numerical characters in both English and Devanagari scripts. The complexities of handwriting differences need a highly accurate distinguishing system that requires the least amount of human interaction to be completed. A multi-objective strategy is proposed to tackle this, which includes Recognition Algorithms for Databases for customized algorithmic design, Classification Assurance for robust pattern classification, Enhanced Transmission of Classifiers for advanced classifier propagation, and Optimization of OCR for language-specific adaptability[66–70]. It is essential to include state-of-the-art technology, especially neural networks. These networks will train from different datasets. Continuous development is ensured via adaptive learning, which also helps the system to become future-proof by allowing it to identify new variants[71–75]. Error correction is made possible via an intuitive interface, which feeds back loops into the system to train it further.

In order to preserve cultural heritage while embracing new technology, the proposed OCR system seeks to detect handwritten English and Devanagari numerals easily. It is suitable in areas including banking, data entry, and educational technology. Pre-processing, feature extraction, categorization, and verification phases are all part of the process that turns handwritten numerical characters into a digital format that computers can understand.

Artificial Intelligence (AI) performs discriminant analysis to classify objects for tasks. Linear Discriminant Analysis (LDA) optimizes deviation between classes and reduces deviation within classes. It may be erroneous for non-linearity problems[76–77]. Models based on NN may be applied to advanced scientific system prediction or medical evaluation. LDA classifiers are used in specific recognition techniques that use binarized MNIST and CPAR databases to categorize data precisely based on Feature Extraction (FE). The architecture of the proposed system is given in **Figure 1**.

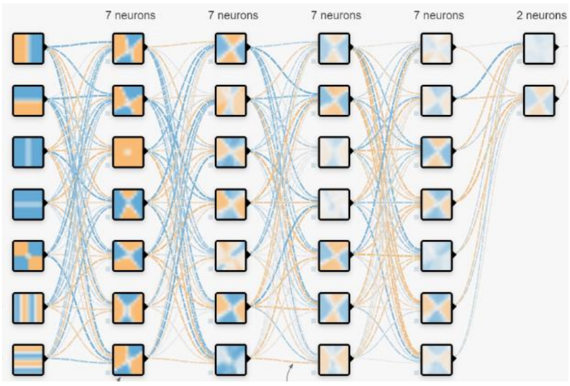


Figure 1. Architecture of neural networks.

3.1. Linear discriminant analysis (LDA)

Two methods, one using a NN-based classifier and the other using LDA, may be used to classify handwritten data. First, preprocessing the data, calculating the class means and scatter matrices, eigenvalue decomposition, choosing the best eigenvectors, and projecting the data onto a reduced-dimensional space are all steps in the LDA approach. The sample means (μ_i) and overall mean (μ) are used to construct the within-class scatter matrix (S_w) and between-class scatter matrix (S_b). The *Top-k* eigenvectors are then chosen. A linear classifier is then trained on the reduced-dimensional space to classify handwritten texts, Equations (1) and (2).

$$s_w = \sum_{i=1}^{C} \sum_{j=1}^{N_i} (x_{ij} - \mu_i)(x_{ij} - \mu_i)^T \quad (1)$$

$$s_b = \sum_{i=1}^{C} N_i(\mu_i - \mu)(\mu_i - \mu)^T \quad (2)$$

Conversely, the classifier based on NN requires preprocessing of the data, design of the architecture, assembly of the models, training, and assessment. A Convolutional Neural Network (CNN) architecture is often used for image classification tasks. The forward pass equations run during the training phase, including activation functions, weights, and biases. Backpropagation is then used to update the weights for better performance.

The approach starts with gathering lapelled dataset and then preprocessing it for neural network and LDA compatibility. The original data trains a NN with the proper layers and activation functions, while LDA decreases the dimensionality and trains a linear classifier. Ultimately, a comparison of the models is conducted, and adjustments are made in light of the assessment outcomes to improve the classification of handwritten documents.

3.2. Dimensionality reduction

High-dimensional data decreases to low-dimensional space while maintaining key parameters. This technique minimises computational costs and enhances data visualisation, thus rendering it common in ML models. Data should be displayed in lower dimensions without removing important features or information. FE or linear transformation represent this method of operation. Unsupervised dimension reduction approaches like Principal Component Analysis (PCA) need not involve information about classes in the training set, but LDA does.

3.3. Algorithm for LDA

- Step 1. The formula used for the d-dimensional mean vector proceeds using the multiple classes of data sets.
- Step 2. The calculation of the two types of scatter matrices (i.e., the class scatter matrices and between classes).
- Step 3. Determining the eigenvalues and eigenvectors of scatter matrices using analysis.
- Step 4. Layered ordering of eigenvalues and eigenvectors is carried out in a sequence of decreasing order.
- Step 5. In order to generate a $d \times k$ dimension matrix 'W', identify the 'k' highest eigenvalues.
- Step 6. Data are used in tandem with the W eigenvector matrix to generate a fresh subspace. The results of the samples $K = 25$ eigen digits formed by the LDA algorithm for MNIST digits are shown in the results section.

4. Result and analysis

In order to increase the accuracy of HWR numerical characters, this article takes advantage of the abundance of data found within two massive databases. The MNIST storage, which has become recognised as a benchmark in the manufacturing sector, provides an extensive collection encompassing 70,000 data. Many accurate models that can manufacture assumptions across various writing styles have benefited immensely from such examples. There are 60,000 data contained within the training database of MNIST, which is a crucial tool for designing and implementing methods. However, the 10,000 data that were saved initially to be evaluated make it feasible to perform a comprehensive evaluation of the functioning of the network.

Moreover, the CPAR data includes a large number of Devanagari scripts as well as integer symbols. Over 80,000 statistics and a remarkable 125,000 symbols are encompassed in its investigation, which is superior to that of MNIST. There is an invention of data that has been uploaded to the MNIST repository. Over 5000 Hindi pangrams have been added to the collection, which is crucial for training models in document analysis. Emphasizing a subset of 1300 numerals from CPAR, each with around 120 unique manifestations, enhances the models' ability to handle handwriting details. Focusing on number recognition from a substantial subset of 40,000 CPAR samples, with 2030 datasets for testing and 3000 for training, the project aims to advance accuracy in OCR. The ultimate goal is a solution adept at reading handwritten digits and adapting to diverse real-world applications.

The Database-Loaded training and testing set:

This method can import the text of a data file into a DataGrid View widget. After selecting the document, it is functional with the Menu and the Open feature. Using the Read Block procedure from the Stream Reader class, the 32 × 32 matrix has been passed to the buffer value. The performance of the iteration ends if either the total amount of digits that have been received is less than the size of the buffer of data that has been set up for the image or the variable that is entrusted with maintaining the line of data that is positioned below the matrix label is empty. The collected text values are stored in an image and inserted in the DataGrid View in the initial training section. The total number of loop interactions ranges from one to five hundred. Within the test section, there were between 1000 and 1500 iterations. Using a bitmap as an input, the FE function converts it into an array of numerals, and any data produced by the process is then imported into the DataGrid View.

Text data to bitmap method:

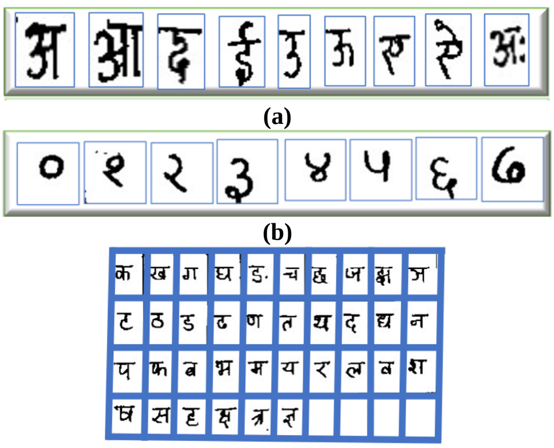
The document is implemented as a parameter in the FE method, which requires a zero-one matrix with dimensions of 16 × 16. The number "0" converts into a white pixel, while the numeral "1" changes into a black pixel. An image in bitmap format is what it outputs in this format.

Bitmap-Based FE text data:

A case study of an overflow of the approach stated previously is the FE method that uses the image bitmap as an input and outputs an array of floating point numbers. Performs a test to determine whether each pixel in an image is white. If this is the scenario, it will type '1'; otherwise, it will type '0'.

Devanagari characters:

India adopts Devanagari, a centuries-old Brahmi script, for Hindi, Marathi, Konkani, and Nepali. The 10 digits and basic symbols comprise 13 vowels and 36 consonants. The fourth most common handwriting method is Devanagari and are different only by a single dot, "vowels" by a tiled line inside a circle, "numbers" look identical, "consonants" look similar. Symbols that include 'क्ष', 'त्र', and 'ज्ञ' originate from 'ग' and 'य' (**Figure 2**).



(a)

(b)

(c)

Figure 2. (a) vowels of devanagari script; **(b)** numerals of devanagari script; **(c)** consonants of devanagari script.

Hindi font includes a middle (core), top, and bottom, so vowel adjectives are significant. The central portion comprises characters with punctuation marks and unique symbols, while the top and bottom are Swar modifiers and diacritic signs. A “SHIRO REKHA” line distinguishes the top and core, and a Purnaviram (full stop) finishes an entire phrase or sentence (**Figure 3**).

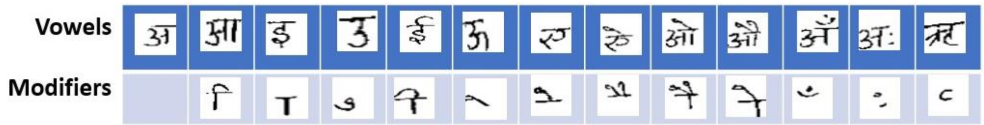


Figure 3. Vowels with corresponding modifiers of Devanagari script.

It is accessible to a straight object with a “VYANJAN” that can be transformed into a half-form in Hindi when two vyanjans are merged. The left side of the original “VYANJAN” with a straight bar is the element that forms the half-form of the phrase “VYANJAN”. **Figure 4** shows an aspect of the “VYANJAN” type indicated in **Figure 2c**. The fact that the associated vowel does not have a half form is demonstrated by the recognition that this figure includes blank substitutes.

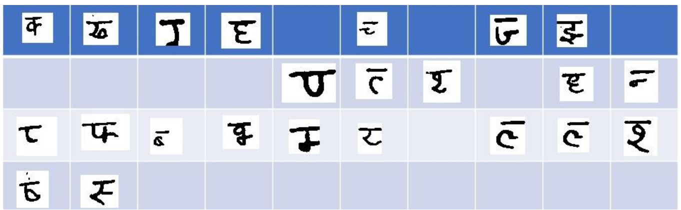


Figure 4. Half form of consonants of Devanagari script.

Different performance patterns are seen in the CNN and LDA designs when the model results are compared. The CNN models display dynamic patterns in the accuracy wave shown throughout epochs, demonstrating varying accuracy rates as training advances. These NN-based models can adapt and learn sophisticated representations from the input across consecutive epochs (**Figure 5**). They are often used for complex pattern recognition tasks. However, throughout epochs, the accuracy wave of the LDA model—a linear dimensionality reduction technique—remains remarkably stable. Because LDA is intended for discriminative analysis, it may achieve a stable classification performance without requiring the repeated modifications that NN need. Notably, it is possible to notice that the LDA accuracy values, produced randomly in this case, vary within a specific range. The comparison study reveals the heterogeneous character of model behaviours, where LDA consistently provides discriminative power and NN changes dynamically throughout epochs. A thorough analysis of the models’ performances on real datasets and validation using relevant metrics would be necessary to get more insights into their behaviours and appropriateness for specific tasks.

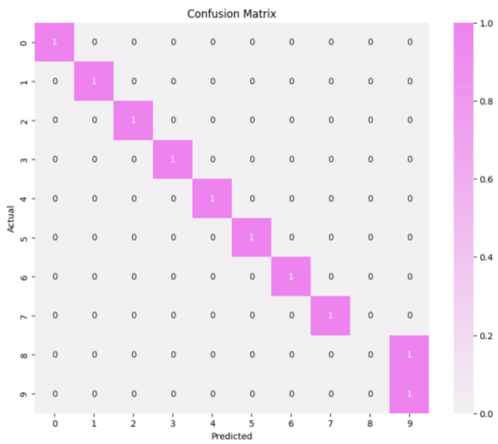


Figure 5. Confusion matrix.

The proposed model was tested on the MNIST dataset, achieving an average accuracy of 98.98% (**Figure 6**). Obtaining an accuracy value of 98.19%, we also completed the cross-dataset evaluation on the CPAR database. The results of this research demonstrate that the CNN classifier is higher in accuracy, with a rating of 99.14%.

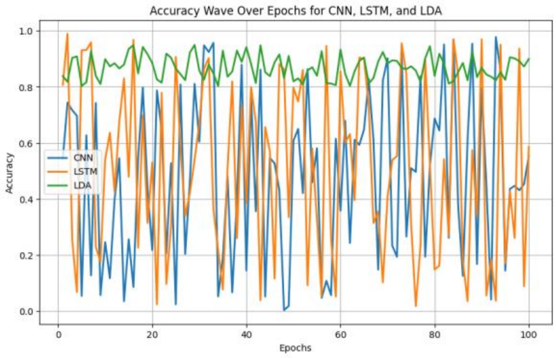


Figure 6. Comparison of accuracy.

5. Conclusion and future work

This article uses Linear Discriminant Analysis (LDA) to analyse HWR numerical characters. The work addresses HWR numerical character similarities and merges and writing tool-induced line thickness and sharpness variations. It additionally highlights numerous training and testing phases for enhanced accuracy. Devanagari numerals were implemented to train the backpropagation neural network but were unsuccessful. Improved pattern identification methods like CNN based on Deep Learning techniques are planned. Data enhancement might additionally enhance the model's handwriting style generalization. Transfer learning might decrease training through the application of pre-existing systems. The model performed 98.98% on the MNIST dataset. In the CPAR database, we completed a cross-dataset evaluation with 98.19% accuracy. The results of this research demonstrate that the CNN classifier is higher in accuracy, with a rating of 99.14%.

Furthermore, using the advantages of cloud-based and smartphone applications makes these features significantly more accessible and available to more people.

Author contributions

Conceptualization, SS and PD; methodology, SS; software, HMAG; validation, NA; formal analysis, SS; investigation, SS; resources, JB; data curation, JA and NA; writing—original draft preparation, SS; writing—review and editing, SS and PD; visualization, JT and JS; supervision, HHAG; project administration, NB; funding acquisition, HHAG. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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