

# Handwritten Malayalam Word recognition Based on Convolutional Neural Networks

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**Abstract:** *This research paper presents a system that can recognize handwritten Malayalam characters and words through the use of convolutional neural networks (CNNs). Handwritten character recognition (HCR) is a complex area of study that involves identifying human handwriting in different languages. While HCRs have been developed for languages such as English, Japanese, and Chinese, the task remains challenging for the languages in India, especially in south Indian languages due to the large character sets, compound characters, modifiers, and curvature shapes of characters in these languages. The main objective of this research is to convert the handwritten Malayalam characters and words containing in the input image into corresponding digital text form. This is achieved by utilizing a trained convolutional neural network (CNN) for converting the handwritten characters and words in the image to corresponding digital form. The recognition system is implemented in Python, with the TensorFlow and Keras frameworks used for developing the CNN model. Additionally, the Open-Source Computer Vision Library (OpenCV) is utilized for performing various operations on the input image. The proposed method also includes a technique for segmenting words and characters from an input image, and predicting characters using the CNN model. Initially, the system aims to identify characters and words, with plans to extend it to recognize complete sentences in the future.*

**Keywords:** Convolutional neural network CNN, Malayalam Characters, OpenCV, Python

## I. INTRODUCTION

In today's world, automation is a critical aspect of many industries, and it is powered by artificial intelligence (AI). Deep learning is one of the most rapidly advancing areas of AI, which has many applications. One such application is character recognition, which involves a computer's ability to interpret handwritten or printed characters from various sources. A Comparative Study on Handwritten Digit Recognition Classifier Using CNN and Machine Learning Algorithms [1], To identify discrete handwritten digits, the algorithm used K-Nearest Neighbor, Support Vector Machine, and Convolutional Neural Networks (CNN). The results show that CNN is the most optimal machine learning technique to classify handwritten digits.

A process called Optical character recognition (OCR) that convert images with printed, typewritten, or handwritten characters into machine-readable digital format, reducing the need for manual work. Handwritten character recognition (HCR) is a challenging task for researchers due to the varying writing styles and languages, such as Malayalam, which has a complex structure and identical character sets[2]. In order to overcome these challenges, several methods have been proposed, such as Artificial Neural Networks, Template Matching, and Hidden Markov Model. One of the most popular deep learning techniques used for classification tasks across various domains, including natural language processing (NLP), face recognition, image classification, and autonomous driving, is the Convolutional Neural Networks (CNNs). Many of recent work ([3]–[7]) used CNN for handwritten text recognition. This research paper proposes a novel CNN model for recognizing Malayalam characters and a method for segmenting words and characters from an image.

## II. LITERATURE SURVEY

A handwritten English alphabet recognition system based on CNN [8] has able to predict the various handwritten alphabets, this model trained using the dataset from Kaggle. The model is developed using TensorFlow as it's back-end and the model has Convolution filters with 3 layers of fully integrated visualization. The Detection accuracy of the model is found to be 97.83%.

In another Handwritten English Character and Digit recognition System by Al-Mahmud, Asnuva Tanvin and Sazia Rahman[9]they constructed a Convolutional Neural Network (CNN) model to recognize handwritten English capital letters and digits, achieved 99.47% accuracy for digits and 98.94 % accuracy for English capital letters.

Vaisakh V K proposed [10] a Malayalam character recognition system that convert the input image containing handwritten character into corresponding digital text. The recognition system uses a trained ANN and is developed using Python programming language, the OpenCV library for image processing operations. In another Malayalam handwritten character recognition system Pranav P Nair [11], recognize only 6 characters using LeNet. A Handwritten Digit Recognition system that recognizes two digit using CNN & Image Processing by Rushikesh Mantri, Dikshant Meshram, Dipti Jadhav [12], the EMNIST dataset is used for recognition. The developed CNN model comprises three layers, that are named by the first one is convolutional layer, sub-sampling layer is the second one, and the third is fully connected layer. The model has demonstrated an accuracy rate of over 90% for digit detection.

Jabir Ali V, Jose T Joseph proposed a CNN based handwritten Malayalam character recognition system [13], that recognize Malayalam characters. The CNN model which used in this study achieved 97.26% accuracy in recognizing Malayalam handwritten characters. An Arabic handwritten character recognition system [14] based on CNN, achieved 97% accuracy on the AHCD dataset and 88% accuracy on the Hijja dataset. In another handwritten Arabic character recognition system [15] utilizes deep learning, the model has 18 layers which include four layers for convolution, four layers pooling, and another four for batch normalization, and dropout, then one layer for Global average pooling and finally a Dense layer. This model trained with AHCD and MadBase dataset, achieved an accuracy of 96.93% and 99.35% respectively.

To identify handwritten Malayalam Digits, Divya konikkara and Uhsa k [16], proposed a CNN model with three layers: Input Layer, Hidden Layer and Classification Layer. The authors achieved an accuracy of 83%. The recognition of Malayalam characters from palm leaves is achieved by employing deep learning techniques [17]. The palm leaves are first subjected to a process that involves segmenting the lines using histogram and contour methods. Following this step, the individual characters are extracted from the segmented lines. To accurately recognize these characters, a specially designed convolutional neural network (CNN) is employed.

A Handwritten Chinese character recognition system [18] based on CNN achieved an accuracy of 97%. A Sinhala Handwritten Character Recognition using CNN [19], around 110,000 image data were used for the experiment. Achieved an overall accuracy of 82.33% for 434 characters. A Handwritten Kannada Character Recognition and Classification Through OCR by utilizing Hybrid Machine Learning Techniques [20], has obtained the accuracy rates 95% for Random Forest, 96% for Support Vector Machine and 92% for K Nearest Neighbors based on 2000 handwritten documents.

Bipin Nair.B.J et al., [21] brought a noval technique that can detect signature, seal and fingerprints on Malayalam agreement papers. They used the detection method that worked with colour space transform and pixel-based contour detection method. The results show a better performance to other methods for various with agreement datasets, with a good average Fscore of 84.9%. Integrating Writing Dynamics in CNN for Online Children Handwriting Recognition [22]. A real child handwriting dataset with 27 000 characters is used and achieved an accuracy of 95%. American and Indian sign language translation using CNN [23], A real time sign language to speech conversion and speech to sign language conversion achieved by an accuracy of 98.34% An Air Writing Recognition of Geometric Shapes using CNN [24], which recognize geometric shapes with an accuracy of 98%. A Gujarati Handwritten Character Recognition from Text Images [25] based on CNN and Multi- Layer Perceptron (MLP). The CNN yields a success rate of 97.21%, while the MLP achieves a rate of 64.48%.

Nitin Gupta presented a platform for Text recognition from handwritten input document based on Machine Learning and Tensor FlowFlow [26]. Their model utilizes a recurrent neural network, convolutional neural network, and a connectionist temporal classification layer to achieve effective text recognition. Machine Learning Based Recognition

of Bangla Handwritten Characters [27], this model trained using CMATERDB dataset and achieved 99.06% accuracy on alphabets, 99.75% accuracy on digits and 99.15% accuracy on special characters.

Handwritten Character Recognition from Images using CNN- ECOC [28], CNN with Error Correcting Output Code (ECOC). The CNN is used for feature extraction and ECOC is for classification. In their study, Malakar et al.[29]employed a segmentation technique to divide the word image into distinct segments. They then extracted elliptical and gradient features from these segments. To identify the most relevant features, the researchers applied a feature selection approach based on a Genetic algorithm (GA) to the extracted local and global features. A Research on Segmenting Character from Malayalam handwritten Documents [30], describing an approach to segment individual characters from Malayalam handwritten documents.

### III. MALAYALAM LANGUAGE

Malayalam is a language spoken by approximately 45 million people worldwide. Malayalam is the language of Indian state Kerala and is one of the 22 recognized languages in India. The Malayalam language shares similarities with other South Indian languages such as Kannada, Telugu, and Tamil in terms of its complex character structure, which includes core characters and vowel diacritics. The script is characterized by curves and holes, and some characters may appear similar with only slight differences. The modern Malayalam script consists of 15 vowel letters and 42 consonants, vowel signs, consonant signs [2]. Additionally, there are conjunct consonants formed by combining other consonants. A dataset of 44 basic Malayalam characters is used here that is displayed in Fig.1.

Independent Vowels									
അ	ആ	ഇ	ഉ	ഋ	എ	ഈ	ഒ		
0D05	0D06	0D07	0D09	0D0B	0D0E	0D0F	0D12		
Consonants									
ക	ഖ	ഗ	ഘ	ങ	ച	ഛ	ജ	ഝ	ഞ
0D15	0D16	0D17	0D18	0D19	0D1A	0D1B	0D1C	0D1D	0D1E
ട	ഠ	ഡ	ഢ	ണ	ത	ഥ	ദ	ധ	ന
0D1F	0D20	0D21	0D22	0D23	0D24	0D25	0D26	0D27	0D28
പ	ഫ	ബ	ഭ	മ	യ	ര	റ	ല	ള
0D2A	0D2B	0D2C	0D2D	0D2E	0D2F	0D30	0D31	0D32	0D33
ഴ	വ	ശ	ഷ	സ	ഹ				
0D34	0D35	0D36	0D37	0D38	0D39				

Fig. 1. Malayalam Characters.

### IV. METHODOLOGY

*A. Deep Learning:* Deep Learning is a subset of machine learning that draws inspiration from the brain's structure and function to develop algorithms, known as Artificial Neural Networks (ANN). One of the benefits of deep learning is that it eliminates the need for manual feature extraction, which is required in classifiers such as Random Forest and SVM. ANNs are capable of extracting features on their own. This study introduces a novel Convolutional Neural Network (CNN) approach for character classification.

*B. Convolutional Neural Network:* A Convolutional Neural Network (CNN) is a specific kind of Artificial Neural Network that has been successful in identifying patterns from two-dimensional data. It is widely used in image classification, natural language processing, and other similar problems. Compared to a regular ANN, CNN uses parameter sharing, making computation much easier. A CNN consist different layers, an input layer, Rectified Linear Unit- ReLU layers, one or more convolution layers, pooling layers, fully connected layers, and an output layer. The complexity of a CNN can vary depending on the specific architecture and classification needs. A basic CNN architecture is illustrated in Fig.2.

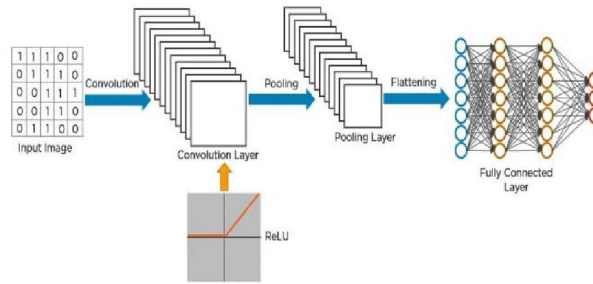


Fig. 2. Convolutional Neural Network.

### V. THE PROPOSED SYSTEM

The system proposed in this study employs a novel CNN model for character classification, with its architecture depicted in Fig.3. This intelligent system is particularly useful for digitizing Malayalam handwritten scripts, as it can accurately recognize the characters and convert them into a digital format. This significantly reduces the need of manual labor for recognizing the characters and data entry for handwritten documents. The four main phases of the system are: Dataset preparation, CNN architecture definition, Training the CNN model , and Model deployment.

#### A. Dataset preparation:

The accuracy of handwritten character recognition is largely dependent on the quality of the dataset used. Regrettably, there is no reliable public database available for Malayalam characters. Nonetheless, a researcher has contributed a dataset of Malayalam character images on Kaggle, this set has been selected as our data set. To increase the dataset size and improve CNN training, some technique such as scaling, shearing, rotation, and translation are applied to the existing images, that result a larger number variations for the dataset.

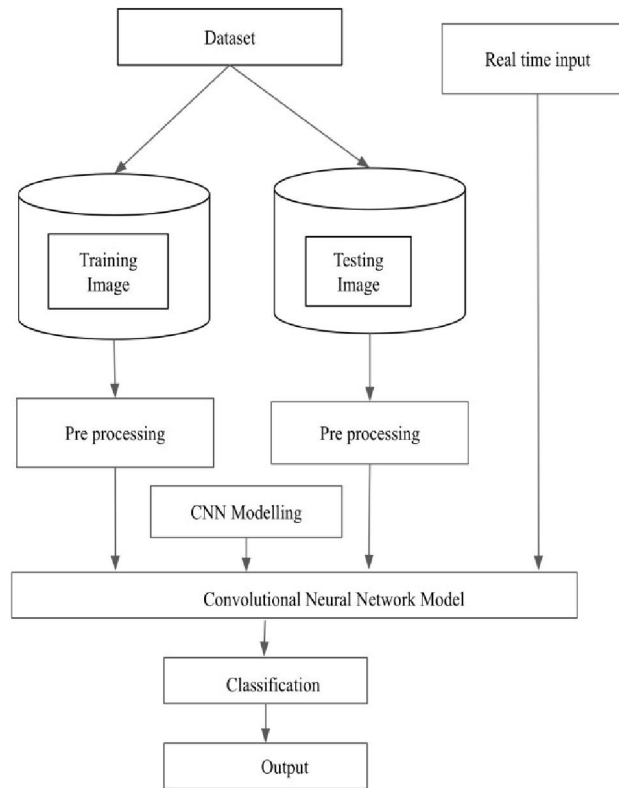


Fig. 3. System Architecture.

**B. CNN Architecture:**

A Convolutional Neural Network (CNN) is implemented in Python for feature extraction and classification of the Malayalam characters. A standard Convolutional Neural Network (CNN) typically comprises several layers: Convolutional layers, Pooling layers, Non-linearity layers, and Fully-connected layers, in addition to the input and output layers.

For our handwritten Malayalam character recognition task, a CNN model is designed with an input size of 86x86x1. It includes convolution layers, pooling layers, normalization layers, fully connected layers, dropout layers in addition to the input and output layers. The model uses filters of different sizes for convolution 3x3, for max-pooling pool size 2x2, and it uses ReLu activation function in the non-linearity layer. To achieve faster global minimum Batch normalization is applied, and the optimizer used for gradient descent during training is Adam. The output layer contains 44 classes, that representing each character in the dataset. Following Fig. 4 and Fig. 5 describing model summary and detailed architecture.

Layer (type)	Output Shape	P
conv2d_16 (Conv2D)	(None, 84, 84, 32)	3
max_pooling2d_16 (MaxPooling2D)	(None, 42, 42, 32)	0
batch_normalization_12 (Batch Normalization)	(None, 42, 42, 32)	1
conv2d_17 (Conv2D)	(None, 40, 40, 64)	1
max_pooling2d_17 (MaxPooling2D)	(None, 20, 20, 64)	0
batch_normalization_13 (Batch Normalization)	(None, 20, 20, 64)	2
conv2d_18 (Conv2D)	(None, 18, 18, 128)	7
max_pooling2d_18 (MaxPooling2D)	(None, 9, 9, 128)	0
batch_normalization_14 (Batch Normalization)	(None, 9, 9, 128)	5
conv2d_19 (Conv2D)	(None, 7, 7, 256)	2
max_pooling2d_19 (MaxPooling2D)	(None, 3, 3, 256)	0
flatten_4 (Flatten)	(None, 2304)	0
dense_16 (Dense)	(None, 512)	1
dropout_12 (Dropout)	(None, 512)	0
dense_17 (Dense)	(None, 1024)	5
dropout_13 (Dropout)	(None, 1024)	0
dense_18 (Dense)	(None, 512)	5
dropout_14 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 44)	2

=====  
 Total params: 2,641,580  
 Trainable params: 2,641,132  
 Non-trainable params: 448

Fig. 4. Model summary

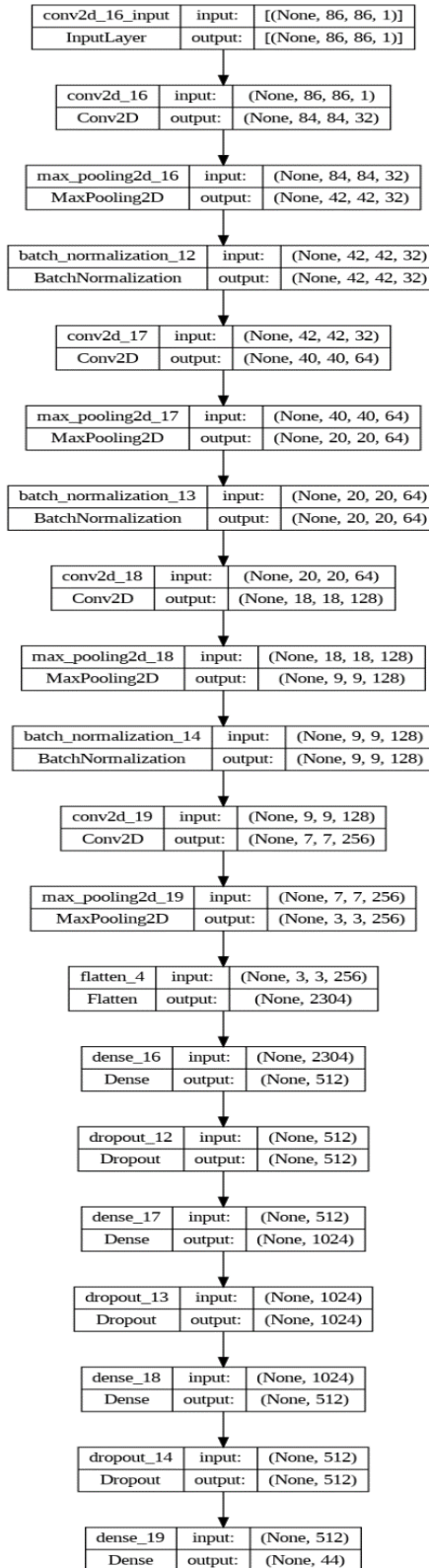


Fig. 5. Model architecture with input–output parameters

**C. Training the CNN Model**

To train the model, the dataset is first processed and converted into a list consisting of NumPy arrays containing images along with their respective labels that have been encoded using one-hot encoding. The dataset is then partitioned into training and testing sets, with a ratio of 80:20. Subsequently, the training set is split into two parts, namely training and validation sets, using the same 80:20 ratio. The sizes of the resulting sets are 58,816 images for training, 14,705 images for validation, and 18,381 images for testing. The validation set is used during training to detect overfitting. To avoid memory inefficiencies, the dataset is divided into batches during training. Once the model is trained successfully, the weights are saved.

The model is saved after successful training. The accuracy of the model is increased and the loss decreased as the number of epochs increased, shown in Fig.6 and Fig.7.

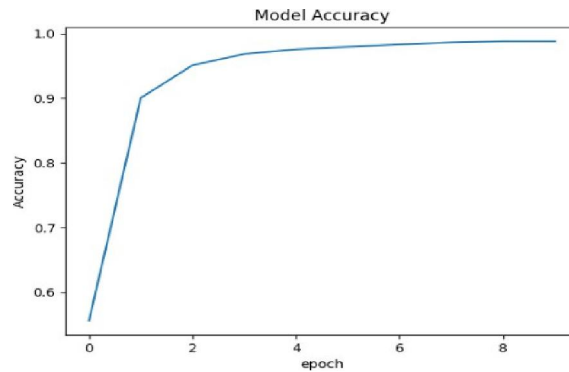


Fig. 6. Model accuracy with no of epoch

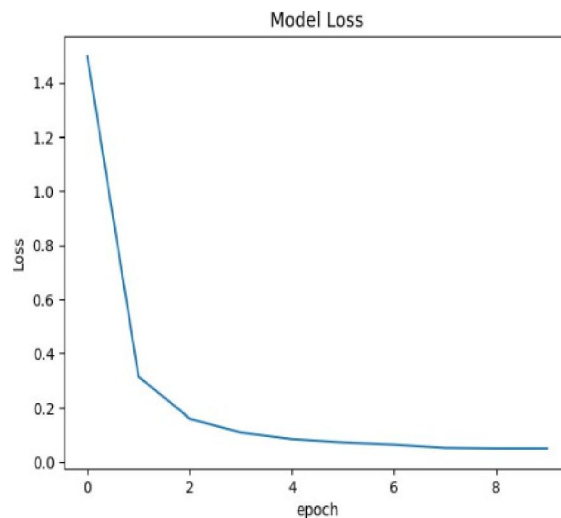


Fig. 7. Model Loss with no of epoch

**D. Deploy the Model**

The trained CNN model needs to be deployed to enable the user to upload real-time input images of handwritten Malayalam script and that generate predictions. The implementation flowchart shown in Fig. 10, outlines the steps involved. First, the image of the handwritten character is read and segmented. The words are separated using appropriate segmentation mechanisms, then separating each character from the words. The segmented characters are then passed through the saved CNN model for prediction. Then associate each predicted class with its respective Unicode representation of Malayalam character. An example of input image is shown in following Fig.8

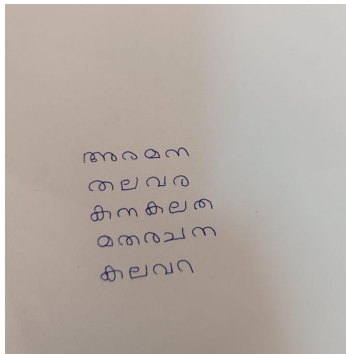


Fig. 8. Input image.

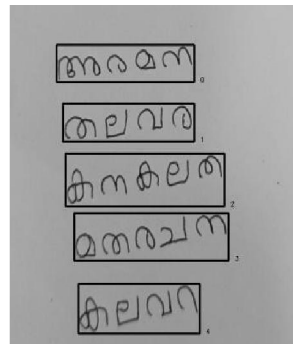


Fig. 9. Bounding box around each word

The segmentation algorithm for handwritten Malayalam characters involves several steps. Firstly, the input image is converted to grayscale. Then, a suitable kernel size is used to apply morphologyEx operation to obtain words as a single contour. Next, the contour bounding boxes as shown in Fig.9 are stored in a list. For each bounding box, a small kernel size is used to apply morphologyEx operation, and the bounding boxes are drawn by detecting contours. The bounding boxes are then sorted in increasing order of x-axis, and the coordinates of each box are cropped from the input image and stored in a list. The flow chart in Fig.10 describing the steps in real time implementation.

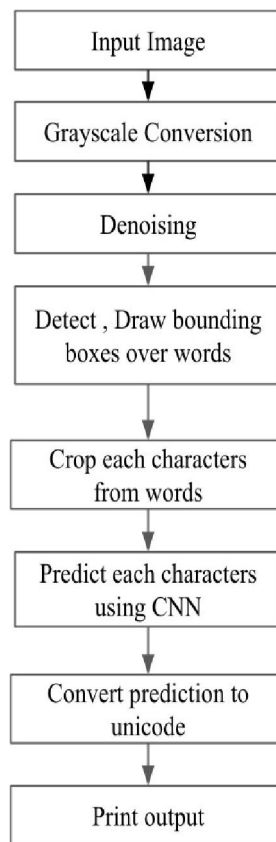


Fig. 10. Deployment of the Model.

## VI. RESULTS AND DISCUSSIONS

A model created using Convolutional Neural Networks (CNNs) to classify the handwritten Malayalam characters. After training on a dataset of images, the CNN model achieved an accuracy rate of 98.84%. The system was implemented utilizing Keras with a Tensorflow backend, and OpenCV was utilized for tasks such as image



acquisition and segmentation. Table 1, displays the precision, recall, and f1-score for each letter, ranging from 0.9 to 1. This means that the classifier performs extremely well in accurately identifying each letters, the overall accuracy of the classifier is 99%.

	precision	recall	f1-score	support
0	1.00	0.99	1.00	353
1	1.00	0.99	0.99	397
2	0.97	0.96	0.97	432
3	0.90	1.00	0.95	421
4	1.00	0.99	0.99	409
5	0.99	1.00	0.99	423
6	1.00	1.00	1.00	439
7	0.99	0.98	0.99	375
8	1.00	0.98	0.99	421
9	0.99	1.00	0.99	413
10	1.00	1.00	1.00	417
11	0.99	0.99	0.99	404
12	0.98	1.00	0.99	402
13	0.98	1.00	0.99	440
14	1.00	1.00	1.00	406
15	1.00	0.99	0.99	462
16	1.00	0.99	1.00	426
17	1.00	1.00	1.00	390
18	0.97	1.00	0.99	444
19	0.99	0.99	0.99	417
20	1.00	0.98	0.99	438
21	1.00	0.99	1.00	340
22	1.00	0.98	0.99	379
23	1.00	0.98	0.99	416
24	0.99	1.00	1.00	443
25	0.98	0.97	0.98	403
26	0.98	1.00	0.99	429
27	0.98	1.00	0.99	418
28	1.00	0.97	0.99	428
29	1.00	0.96	0.98	457
30	1.00	0.98	0.99	426
31	0.94	1.00	0.97	459
32	1.00	0.97	0.99	423
33	0.99	0.99	0.99	425
34	1.00	0.96	0.98	465
35	0.97	0.99	0.98	403
36	0.99	0.99	0.99	396
37	1.00	0.98	0.99	434
38	1.00	0.99	0.99	394
39	1.00	0.99	0.99	434
40	0.98	1.00	0.99	427
41	0.99	1.00	0.99	421
42	0.99	0.99	0.99	437
43	0.99	1.00	0.99	395
micro avg	0.99	0.99	0.99	18381
macro avg	0.99	0.99	0.99	18381
weighted avg	0.99	0.99	0.99	18381
samples avg	0.99	0.99	0.99	18381

Table 1. Classification report

An algorithm was proposed to process real-time input images of Malayalam handwritten characters, it includes acquiring the image, converting it to grayscale, binarizing it, segmenting words and characters, and finally making predictions. The output prediction for a real time input image shown Fig.11, corresponding output texts shown in Fig.12



Fig. 11. Output Prediction for a real time input image.



Fig. 12. The Generated Output texts.

### VII. CONCLUSION AND FUTURE WORK

Handwritten character recognition (HCR) has many useful applications, including office automation. Convolutional neural networks (CNNs) are the most effective approach for image recognition and classification. However, the current HCR system is limited to identifying only forty four Malayalam characters and words with those characters. In the future, the model can be improved to recognize a wider range of glyphs and diacritics present in the Malayalam language, and also to properly recognize characters present in the connected handwritings, as well as vowel diacritics from a script. Moreover, the model's capabilities can be extended to identifying sentences and paragraphs in Malayalam.

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### REFERENCES

- [1]. T. Kumari, Y. Vardan, P. Giridhar Shambharkar, and Y. Gandhi, "Comparative Study on Handwritten Digit Recognition Classifier Using CNN and Machine Learning Algorithms," in *Proceedings - 6th International Conference on Computing Methodologies and Communication, ICCMC 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 882–888. doi: 10.1109/ICCMC53470.2022.9753756.
- [2]. B. Jose and K. P. Pushpalatha, "Malayalam Handwritten Character Recognition Using Transfer Learning," in *2023 International Conference on Advances in Intelligent Computing and Applications, AICAPS 2023*, Institute of Electrical and Electronics Engineers Inc., 2023. doi: 10.1109/AICAPS57044.2023.10074586.

- [3]. A Narayan and R. Muthalagu, "Image Character Recognition using Convolutional Neural Networks," in *Proceedings of 2021 IEEE 7th International Conference on Bio Signals, Images and Instrumentation, ICBSII 2021*, Institute of Electrical and Electronics Engineers Inc., Mar. 2021. doi: 10.1109/ICBSII51839.2021.9445136.
- [4]. D. Chaudhary and K. Sharma, *Hindi Handwritten Character Recognition using Deep Convolution Neural Network*.
- [5]. C. Zhang, Z. Zhou, and L. Lin, "Handwritten Digit Recognition Based on Convolutional Neural Network," in *Proceedings - 2020 Chinese Automation Congress, CAC 2020*, Institute of Electrical and Electronics Engineers Inc., Nov. 2020, pp. 7384–7388. doi: 10.1109/CAC51589.2020.9326781.
- [6]. Khandokar, M. Hasan, F. Ernawan, S. Islam, and M. N. Kabir, "Handwritten character recognition using convolutional neural network," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Jun. 2021. doi: 10.1088/1742-6596/1918/4/042152.
- [7]. R. Panda, S. Dash, S. Padhy, and M. Nayak, "CNN Based Handwritten Odia Character Recognition," in *Proceedings - 2022 International Conference on Machine Learning, Computer Systems and Security, MLCSS 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 267–273. doi: 10.1109/MLCSS57186.2022.00056.
- [8]. S. K. Singh, R. Alam, L. Sujihelen, K. L. Josila Grace, M. P. Selvan, and S. Jancy, "Handwritten Character Recognition using Convolutional Neural Network," in *2022 6th International Conference on Trends in Electronics and Informatics, ICOEI 2022 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 1108–1112. doi: 10.1109/ICOEI53556.2022.9777140.
- [9]. Al-Mahmud, A. Tanvin, and S. Rahman, "Handwritten English Character and Digit Recognition," in *Proceedings of International Conference on Electronics, Communications and Information Technology, ICECIT 2021*, Institute of Electrical and Electronics Engineers Inc., 2021. doi: 10.1109/ICECIT54077.2021.9641160.
- [10]. V. K. Vaisakh and L. B. Das, "Handwritten Malayalam Character Recognition System using Artificial Neural Networks," in *2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science, SCEECS 2020*, Institute of Electrical and Electronics Engineers Inc., Feb. 2020. doi: 10.1109/SCEECS48394.2020.101. IEEE Staff, *2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)*. IEEE, 2017.
- [11]. R. Mantri, D. Meshram, A. Kawale, and D. Jadhav, "Handwritten Digit Recognition for Two Digits Using CNN & Image Processing," in *2022 IEEE 3rd Global Conference for Advancement in Technology, GCAT 2022*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/GCAT55367.2022.9971988.
- [12]. J. Ali and J. T. Joseph, "A Convolutional Neural Network based Approach for Recognizing Malayalam Handwritten Characters," *Int J Sci Eng Res*, vol. 9, 2018, [Online]. Available: <http://www.ijser.org>
- [13]. N. Altwaijry and I. Al-Turaiki, "Arabic handwriting recognition system using convolutional neural network," *Neural Comput Appl*, vol. 33, no. 7, pp. 2249–2261, Apr. 2021, doi: 10.1007/s00521-020-05070-8.
- [14]. M. Kamal, F. Shaiara, C. M. Abdullah, S. Ahmed, T. Ahmed, and Md. H. Kabir, "Huruf: An Application for Arabic Handwritten Character Recognition Using Deep Learning," Institute of Electrical and Electronics Engineers (IEEE), Mar. 2023, pp. 1131–1136. doi: 10.1109/iccit57492.2022.10054769.
- [15]. D. Konikkara and K. Usha, "Malayalam Digit Recognition Using CNN," in *Proceedings of the 2022 3rd International Conference on Intelligent Computing, Instrumentation and Control Technologies: Computational Intelligence for Smart Systems, ICICIT 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 470–473. doi: 10.1109/ICICIT54557.2022.9917967.
- [16]. R. Sivan, T. Singh, and P. B. Pati, "Malayalam Character Recognition from Palm Leaves Using Deep-Learning," Institute of Electrical and Electronics Engineers (IEEE), Mar. 2023, pp. 134–139. doi: 10.1109/ocit56763.2022.00035.
- [17]. W. H. Liu, K. Ming Lim, and C. P. Lee, "Visually Similar Handwritten Chinese Character Recognition with Convolutional Neural Network," in *2021 9th International Conference on Information and Communication*

- Technology, ICoICT 2021*, Institute of Electrical and Electronics Engineers Inc., Aug. 2021, pp. 175–179. doi: 10.1109/ICoICT52021.2021.9527449.
- [18]. J. Mariyathas, V. Shanmuganathan, and B. Kuhaneswaran, “Sinhala Handwritten Character Recognition using Convolutional Neural Network,” in *Proceedings of ICITR 2020 - 5th International Conference on Information Technology Research: Towards the New Digital Enlightenment*, Institute of Electrical and Electronics Engineers Inc., Dec. 2020. doi: 10.1109/ICITR51448.2020.9310914.
- [19]. D. K. Gowda and V. Kanchana, “Kannada Handwritten Character Recognition and Classification Through OCR Using Hybrid Machine Learning Techniques,” in *IEEE International Conference on Data Science and Information System, ICDSIS 2022*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/ICDSIS55133.2022.9915906.
- [20]. B. J. Bipin Nair and A. K. Raj, “Identification of Seal, Signature and Fingerprint from Malayalam Agreement Documents using Connected Component Analysis,” in *Proceedings - 6th International Conference on Computing Methodologies and Communication, ICCMC 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 1279–1285. doi: 10.1109/ICCMC53470.2022.9754150.
- [21]. S. Corbille, E. Fromont, E. Anquetil, and P. Nerdeux, “Integrating Writing Dynamics in CNN for Online Children Handwriting Recognition,” in *Proceedings of International Conference on Frontiers in Handwriting Recognition, ICFHR*, Institute of Electrical and Electronics Engineers Inc., Sep. 2020, pp. 270–275. doi: 10.1109/ICFHR2020.2020.00057.
- [22]. A. Rustagi, Shaina, and N. Singh, “American and Indian Sign Language Translation using Convolutional Neural Networks,” in *Proceedings of the 8th International Conference on Signal Processing and Integrated Networks, SPIN 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 646–651. doi: 10.1109/SPIN52536.2021.9566105.
- [23]. S. P. Samprithi and B. Niranjana Krupa, “Air Writing Recognition of Geometric Shapes using CNN,” in *INDICON 2022 - 2022 IEEE 19th India Council International Conference*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/INDICON56171.2022.10039851.
- [24]. J. Pareek, D. Singhania, R. R. Kumari, and S. Purohit, “Gujarati Handwritten Character Recognition from Text Images,” in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 514–523. doi: 10.1016/j.procs.2020.04.055.
- [25]. N. Gupta and N. Goyal, “Machine Learning Tensor Flow Based Platform for Recognition of Hand Written Text,” in *2021 International Conference on Computer Communication and Informatics, ICCCI 2021*, Institute of Electrical and Electronics Engineers Inc., Jan. 2021. doi: 10.1109/ICCCI50826.2021.9402622.
- [26]. S. A. Niloy, T. S. Bhuiyan, F. I. Leha, S. Imon, and M. Khan, “Machine Learning based Recognition of Bangla Handwritten Characters,” in *4th International Conference on Inventive Research in Computing Applications, ICIRCA 2022 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 1748–1752. doi: 10.1109/ICIRCA54612.2022.9985714.
- [27]. M. B. Bora, D. Daimary, K. Amitab, and D. Kandar, “Handwritten Character Recognition from Images using CNN-ECOC,” in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 2403–2409. doi: 10.1016/j.procs.2020.03.293.
- [28]. S. Malakar, M. Ghosh, S. Bhowmik, R. Sarkar, and M. Nasipuri, “A GA based hierarchical feature selection approach for handwritten word recognition,” *Neural Comput Appl*, vol. 32, no. 7, pp. 2533–2552, Apr. 2020, doi: 10.1007/s00521-018-3937-8.
- [29]. H. C. P, A. Jossy, and A. John, “Segmenting Characters from Malayalam Handwritten Documents.”