**Khazanah Journal of Religion and Technology**
Universitas Islam Negeri Sunan Gunung Djati Bandung, Indonesia
https://journal.uinsgd.ac.id/kjrt
Online ISSN: 2987-6060
Volume 2 Issue 1 (2024)
DOI: https://doi.org/10.15575/kjrt.v2i1.812

# Classifying *Hijaiyah* Letters Handwritten Detection of Children Using CNN Algorithm

Ahmad Maulidi Roofiad
*Department of Informatics*
UIN Sunan Gunung Djati Indonesia
Bandung, Indonesia
1197050009@student.uinsgd.ac.id

Aprian Nur Rohman
*Department of Informatics*
UIN Sunan Gunung Djati Indonesia
Bandung, Indonesia
1217050018@student.uinsgd.ac.id

Annisa Sabillah
*Department of Informatics*
UIN Sunan Gunung Djati Indonesia
Bandung, Indonesia
1217050016@student.uinsgd.ac.id

Elmi Wahyu Triyani
*Department of Informatics*
UIN Sunan Gunung Djati Indonesia
Bandung, Indonesia
1217050045@student.uinsgd.ac.id

*Abstract*— Learning the *Hijaiyah* letters is an important basis because in learning the Qur'an, these abilities must be mastered before they can be introduced and taught to children. However, the recognition of *Hijaiyah* letters in children's handwriting is still a challenge due to the variations and inconsistencies that are often found. Deep learning technology, particularly Convolutional Neural Network (CNN), has demonstrated its ability to classify letters with a high degree of accuracy. Therefore, this research aims to develop a CNN-based *Hijaiyah* letter classification model to help children learn to write and read *Hijaiyah* letters properly. This research uses a CNN model that is optimized with data augmentation techniques and hyperparameter tuning. The model was trained using a standard dataset totaling 1,740 samples of *Hijaiyah* letters. Model evaluation is done by calculating accuracy, precision, recall, and F1-Score on the validation dataset. The results showed that the proposed CNN model achieved almost 94.35% accuracy on the validation dataset. This research is expected to improve children's ability to learn *Hijaiyah* letters.

***Keywords- Children's Handwriting; Classification; CNN; Deep Learning; Hijaiyah Letters.***

## I. INTRODUCTION

Today, Arabic letters have become a necessity in many applications due to the changing times that shift traditional education to digital education [1]. The complexity of Arabic letters, such as the cursive nature from right to left and the use of harakat (punctuation marks), makes the technology for Arabic letters more complicated, especially for children [2]. Although there have been researchers developing handwriting detection technology on Arabic letters, there are still few who focus on children's handwriting. Children's handwriting is generally not neat and consistent. The Qur'an is written in Arabic, so learning the *Hijaiyah* letters well is an important step before reading the Qur'an [3].

Currently, Convolutional Neural Network (CNN) is recognized as a superior method in handwritten character recognition, both in terms of accuracy and efficiency. Distinctive and representative features of images are automatically detected and extracted by CNN, outperforming classical Machine Learning algorithms that require manual definition of features. Therefore, CNNs achieve better results with large data sets and many classes [4]. Y. A. Gerhana et al. [5] claim that the performance of the CNN algorithm in classifying sound data and MFCC in extracting the sound characteristics of the *Hijaiyah* letters is influenced by several factors, such as intonation, incorrect pronunciation of the letters (*makhorijul* letters), and the similarity of the consonant sounds of the letters. A. Rahmatulloh et al. [3] use the Convolutional Neural Network (CNN) algorithm with ADAM algorithm optimization and data augmentation techniques to classify *Hijaiyah* writing characters. The datasets used are Hijja and Arabic Handwritten Characters Dataset (AHCD). As a result, the model achieved 91% accuracy on the Hijja dataset and 98% on the AHCD dataset. D. Muhya [6] claimed that research using hybrid-CNN with

CatBoost was successfully developed to classify *Hijaiyah* letters. The CNN model is trained first to function as a good feature extractor. The feature extraction results are taken from one layer before the model output layer. The results of this feature extraction are then used to train and test the CatBoost model. The hybrid CNN model with CatBoost provided an accuracy value of 96.07%.

Therefore, in this paper, we detail the development of a deep learning-based model using the *Hijaiyah* Handwriting dataset, which consists of 1,740 samples. The dataset is divided into 56 samples per letter for training and 14 samples per letter for testing. This classification system aims to detect and classify *Hijaiyah* letters in children's handwriting effectively. This research makes the following contributions: (1) Develop an improved *Hijaiyah* letter classification model based on CNN, which addresses the gap in the classification of children's handwriting; (2) Conduct a comparative study of the performance of the developed model with existing models; and (3) Developed a prototype called Huroofy, which integrates the best model into a website to help children practice Arabic writing and spelling skills by providing feedback based on their answers.

The rest of the paper is organized as follows: Section II presents a literature review of related research; Section III discusses the proposed algorithm; Section IV presents its results and analysis; and finally, Section V presents conclusions and future research directions.

## II. RELATED WORKS

Many studies have focused on letter identification, including Arabic *Hijaiyah* letters handwritten by children. However, the approaches used are still limited, so the recognition of handwritten characters of *Hijaiyah* letters in children is still lacking compared to other letters. However, some studies have shown that using deep learning models with Convolutional Neural Network (CNN) gives quite good results.

For instance, Y. A. Gerhana et al. [5] claim the impact of intonation and letter pronunciation on the classification performance of Hijaiyah letters using CNN. Similarly, A. Rahmatulloh, et al. [3] use the Convolutional Neural Network (CNN) algorithm with ADAM algorithm optimization and data augmentation techniques to classify *Hijaiyah* writing characters. The datasets used are Hijja and Arabic Handwritten Characters Dataset (AHCD). As a result, the model achieved 91% accuracy on the Hijja dataset and 98% on the AHCD dataset. D. Muhya [6] said that research using hybrid-CNN with CatBoost was successfully developed to classify *Hijaiyah* letters. The CNN model is trained first to function as a good feature extractor. The feature extraction results are taken from one layer before the model output layer. The results of this feature extraction are then used to train and test the CatBoost model. The hybrid CNN model with CatBoost provided an accuracy value of 96.07%.

Other researchers, N. Saqib et al. [7], presented a CNN model for handwritten character recognition (HCR) and then tested this model with MNIST and Kaggle alphabet datasets. The best model used the Adam optimizer with a learning rate (LR) of 0.00001 for the Kaggle dataset, which achieved 99.563% accuracy. As for the MNIST dataset, the model with the 'RMSprop' optimizer and LR 0.001 achieved 99.642% accuracy. N. Wagaa et al. [8] presented a Convolutional Neural Network (CNN) model to recognize Arabic handwritten character datasets. The model was trained on two Arabic datasets, namely AHCD and Hijja. With fine-tuning of the network hyperparameters, we achieved 96.73% accuracy on AHCD and 88.57% on Hijja. A. B. Durayhim et al. [9] claim that the CNN model achieved 99% accuracy in classifying letters using the Hijja dataset for children's handwriting.

S. U. Masruroh et al. [10] concluded that all the top models from various CNN architectures used Adam's optimizer instead of SGD to classify the Hijja and AHCD datasets. This study shows that VGG16 with Adam's optimizer and a learning rate of 0.0001 in fine-tuning provides the best performance in recognizing Arabic writing by children, which tends to be more difficult to classify.

M. S. Alwagdani et al. [11] presented a CNN model used for children's Arabic handwritten character recognition and tested various datasets, including handwritten characters of children, adults and their combinations. The model trained with a dataset that included both groups achieved the highest average accuracy of 92.78%. In distinguishing between children's and adults' handwriting, using additional HOG-based and statistical features improved model performance, with the optimal feature fusion approach achieving an average accuracy of 92.29%.

A. M. H. Azis et al. [12] conveyed that the algorithms used, namely CNN and XGBoost with MFCC, RASTA-PLP, and LPC feature extraction, were effective in classifying the properties of *Hijaiyah* letters with an overall average accuracy of 73.79%. I. Khandokar et al. [13] presented the CNN deep learning technique for handwritten character recognition on the NIST dataset. The accuracy obtained increased from 65.32% with 200 training images to 92.91% with 1000 training images.

Based on existing research, we aim to address the gap in classifying the *Hijaiyah* letters written by children. Our approach specifically targets the unique challenges created by children's inconsistent and sloppy handwriting. We utilize CNN-based models due to their proven efficacy in feature extraction and classification.

The CNN architecture is optimized using techniques such as data augmentation and hyperparameter tuning inspired by the methodology of A. Rahmatulloh et al. [3]. By comparing our model's performance with existing benchmarks, we demonstrated significant improvements in terms of accuracy and efficiency and validated the effectiveness of our approach in the specific context of children's handwriting.

## III. RESEARCH METHODS

### A. Dataset

The dataset we used in this study consists of 1,740 *Hijaiyah* handwriting samples. However, these samples were not collected based on children's handwriting; rather, they were collected from standardized sources to ensure the consistency and quality of the data. The dataset consists of 56 samples per letter for training and 14 samples per letter for testing. Although not taken from a dataset that is not written by children, the development of this model can accurately classify *Hijaiyah* letters that can later be tested on children's handwriting. The example of the handwriting dataset of *Hijaiyah* is provided in Figure 1.

Fig 1. The Example of Dataset

## B. *Convolutional Neural Network (CNN)*

Convolutional Neural Network (CNN) has proven to be effective in recognizing various types of handwriting, including Arabic characters. Therefore, by utilizing the success of the CNN algorithm, our proposed model aims to classify *Hijaiyah* handwriting accurately. The model is trained on a dataset of standard *Hijaiyah* handwriting samples to ensure consistency and that the training data is of high quality. Our proposed CNN deep learning model consists of multiple layers designed for effective feature extraction and classification. The following is a breakdown of the model architecture:

### 1) *Convolutional Layers*

This model starts with a series of convolutional layers, each of which is followed by a ReLu activation function to introduce non-linearity and speed up the training phase. The layers are configured to detect various features such as edges, corners, and texture of the input image. The following is a series of convolutional layer stages:

a) ***Convolutional Layers 1 and 2****: The 150×150×3 input image is processed with filters to generate a feature map. The first convolutional layer uses 32 filters with a kernel size of 3×3, followed by a max-pooling layer to reduce the spatial dimension of the feature map.*
b) ***Convolutional Layer 3:*** *This layer applies 64 filters with a kernel size of 3×3, followed by another max-pooling layer. This arrangement helps to extract high-level features from the image.*
c) ***Convolutional Layer 4:*** *Similar to the previous layer, this layer applies 128 filters with a kernel size of 3×3 and is followed by a max-pooling layer, which further reduces the size of the feature map.*
d) ***Convolutional Layer 5:*** *This layer applies 256 filters with a kernel size of 3×3 and includes a max-pooling layer to ensure the extracted features are concise and informative.*

### 2) *Fully Connected Layers*

After the convolutional layer, the model includes a fully connected (dense) layer to combine the features extracted by the convolutional layer. The dense layer is responsible for learning the non-linear combination of features and making the final classification. The averaged output of the final convolutional layer is fed into the dense layer with 512 neurons and a ReLU activation function. The final dense layer uses the softmax activation function to classify the input image into one of the 30 *Hijaiyah* letter classes.

### 3) *Model Compilation and Training*

The model is compiled using Adam's optimizer and a sparse categorical cross-entropy loss function. This setup becomes an effective solution for multi-class classification problems. The model is then trained on the training dataset, with a portion of the data reserved for validation to monitor the training process and prevent overfitting.

### 4) *Evaluation and Saving the Model*

After training, the model is evaluated on the validation dataset to assess its performance. The accuracy and loss of the model are visualized to understand its learning behavior and identify signs of overfitting. In the last step, the trained model is saved for future use.

## IV. RESULT AND DISCUSSION

The CNN model's training process for handwritten Hijaiyah character recognition demonstrates excellent performance. The model was trained using the Adam optimizer and sparse categorical cross-entropy loss over 105 epochs. The hyperparameter setting of the CNN model in this research is shown in Figure 2.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 max_pooling2d (MaxPooling2  (None, 74, 74, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 36, 36, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 17, 17, 128)       0
 g2D)

 conv2d_3 (Conv2D)           (None, 15, 15, 256)       295168

 max_pooling2d_3 (MaxPoolin  (None, 7, 7, 256)         0
 g2D)

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 512)               6423040

 dense_1 (Dense)             (None, 30)                15390

=================================================================
Total params: 6826846 (26.04 MB)
Trainable params: 6826846 (26.04 MB)
Non-trainable params: 0 (0.00 Byte)
```

Fig 2. CNN Architecture

The accuracy graph shows that both the training and validation accuracy metrics increased consistently, with a rapid increase and reaching an accuracy value of 94.35%. This indicates that the model successfully learned the data patterns without overfitting, as the validation accuracy continued to increase along with the training accuracy. The loss graph shows that both the training and validation losses decreased significantly, then stabilized around 20 epochs, indicating normal behavior with no signs of overfitting. Figures 3 and 4 are the accuracy and loss graphs during the training process.

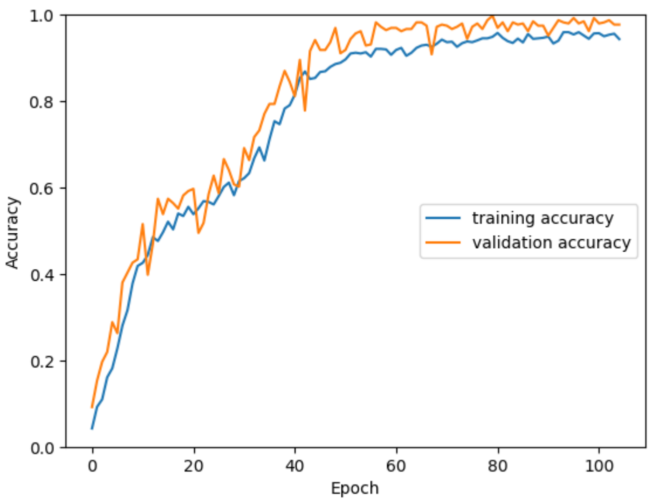


Fig 3. Accuracy Result

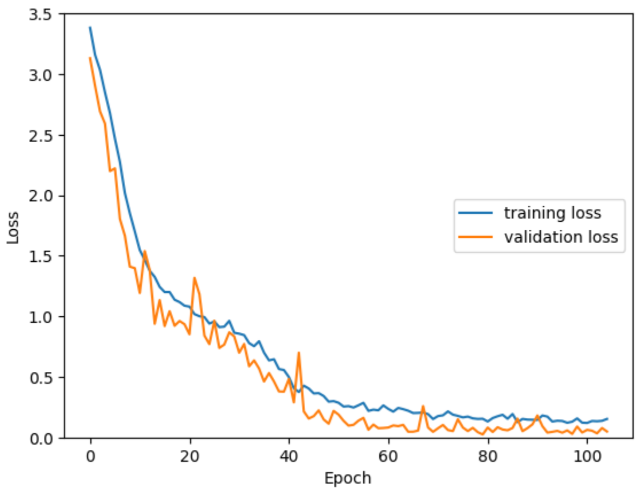


Fig 4. Loss Result

The evaluation was conducted by calculating the confusion matrix and the classification report. The confusion matrix shows that the model could classify almost all characters correctly. Each diagonal element indicates the number of correct predictions for each character class, with each main diagonal element having a value of 14. This means the model perfectly predicted 14 samples for each class in the validation dataset. The results from the classification report evaluation show that our model performed well. Each class in the dataset, consisting of 28 Arabic character classes, has precision, recall, and F1-score of 1.00. This indicates that our model made no mistakes in classifying each class and successfully captured all instances that should belong to each class. The overall accuracy of the model reached 94.35%, indicating that out of a total of 420 samples evaluated, there was not a single incorrect prediction. These results highlight the effectiveness of the CNN model in classifying standard *Hijaiyah* letters and its potential adaptation to children's handwriting.

The assumption in this study is that the CNN model optimized by data augmentation and hyperparameter tuning is able to classify *Hijaiyah* letters accurately, even though the training data does not include children's handwriting. In addition, the data set used for training and validation is representative enough to develop a generalizable model. CNN models, when properly trained and optimized, can effectively classify *Hijaiyah* letters with high accuracy. The use of deep learning techniques is expected to outperform traditional methods both in terms of accuracy and efficiency. Figure 5 shows the example of *Hijaiyah* prediction for “Kho” letter.

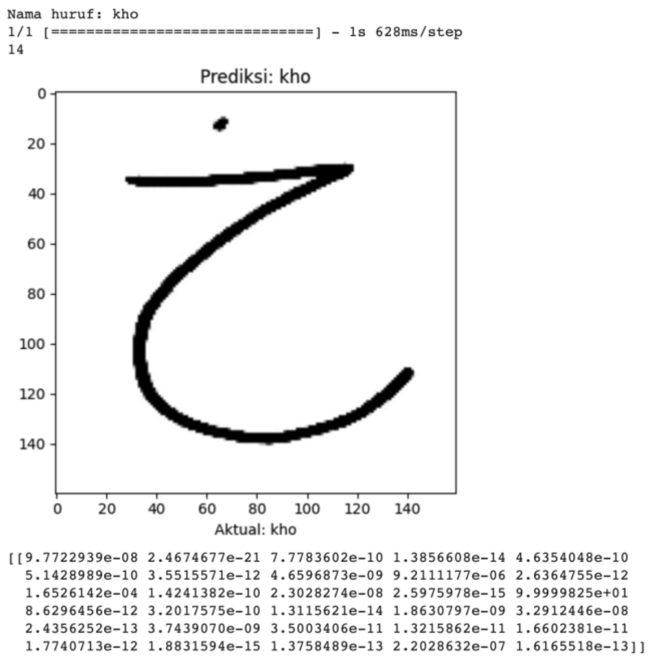


Fig 5. The Example of Prediction

## V. CONCLUSION

This research shows that the Convolutional Neural Network model is very effective in classifying *Hijaiyah* letters, with the ability to achieve almost perfect accuracy. This ability was demonstrated through a series of studies that tested the performance of CNN on a diverse dataset of *Hijaiyah* letter images. Although the training dataset used did not include children's handwriting, the results showed that this model has the potential to overcome the variability and inconsistencies found in the data.

However, a limitation of this study is the lack of representation of children's handwriting in the training dataset. This raises the concern that the performance of the CNN model that proved effective in the study may not translate directly to the real world, where it has to deal with a much wider variety of children's handwriting. However, this research makes a significant contribution to the field of handwriting recognition by producing an accurate CNN model for *Hijaiyah* letter classification. This model has promising implications for the development of innovative and effective learning tools to help children learn *Hijaiyah* letters more easily and enjoyably.

In the future, future research should explore the application of this CNN model on a specially developed dataset of children's handwriting datasets. This will allow for a more comprehensive validation of the model's effectiveness and increase confidence in its ability to perform accurately in real-world scenarios. In addition, the integration of more advanced machine learning techniques or hybrid models that combine CNN with other algorithms can improve the accuracy and robustness of the model to variations in children's handwriting. This could pave the way for the development of more advanced *Hijaiyah* letter recognition systems, which could provide significant benefits to Arabic language education and Islamic literacy.

Overall, this research shows great potential for the Convolutional Neural Network model to revolutionize the way we recognize and classify *Hijaiyah* letters. With further research and development, this technology can open up opportunities to improve Arabic language learning and Islamic Literacy, especially for children.

## REFERENCES

[1] M. Shams, A. A. Elsonbaty, and W. Z. ElSawy, “Arabic Handwritten Character Recognition based on Convolutional Neural Networks and Support Vector Machine,” IJACSA, vol. 11, no. 8, 2020, doi: 10.14569/IJACSA.2020.0110819.

[2] 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,” arXiv preprint arXiv:2212.08610 [cs.CV], 2022, doi: 10.48550/arXiv.2212.08610.

[3] A. Rahmatulloh, R. I. Gunawan, I. Darmawan, R. Rizal, and B. Z. Rahmat, “Optimization of *Hijaiyah* Letter Handwriting Recognition Model Based on Deep Learning,” ICADEIS, 2022, doi: 10.1109/ICADEIS56544.2022.10037496.

[4] N. Alrobah, and S. Albahli, “A Hybrid Deep Model for Recognizing Arabic Handwritten Characters,” IEEE Access, vol. 9, pp. 87058-87069, 2021, doi: 10.1109/ACCESS.2021.3087647.

[5] Y. A. Gerhana, A. M. H. Azis, D. R. Ramdania, W. B. Dzulfikar, A. R. Atmadja, D. Suparman, and A. P. Rahayu, “Automatic Detection of *Hijaiyah* Letters Pronunciation using Convolutional Neural Network Algorithm,” JOIN: J. Online Informatika, vol. 7, no. 1, pp. 123-131, 2022, doi: 10.15575/join.v7i1.882.

[6] D. Muhya, “Classification of *Hijaiyah* Letters Using Hybrid CNN-CatBoost,” INTELMATICS, vol. 3, no. 2, pp. 39-44, 2023, doi: 10.25105/itm.v3i2.17521.

[7] N. Saqib, K. F. Haque, V. P. Yanambaka, and A. Abdelgawad, “Convolutional-Neural-Network-Based Handwritten Character Recognition: An Approach with Massive Multisource Data,” Algorithms, vol. 15, no. 4, 2022, doi: 10.3390/a15040129

[8] N. Wagaa, H. Kallel, and N. Mellouli, “Improved Arabic Alphabet Characters Classification Using Convolutional Neural Networks (CNN),” Computational Intelligence and Neuroscience, 2022, doi: 10.1155/2022/9965426.

[9] A. B. Durayhim, A. Al-Ajlan, I. Al-Turaiki, and N. Altwaijry, “Towards Accurate Children’s Arabic Handwriting Recognition via Deep Learning,” Appl. Sci., vol. 13, no. 3, p. 1692, 2023, doi: 10.3390/app13031692.

[10] S. U. Masruroh, M. F. Syahid, F. Munthaha, A. T. Muharram, and R. A. Putri, “Deep Convolutional Neural Networks Transfer Learning Comparison on Arabic Handwriting Recognition System,” JOIV: Int. J. Inform. Visualization, vol. 7, no. 2, pp. 330-337, 2023, doi: 10.30630/joiv.7.2.1605.

[11] M. S. Alwagdani, and E. S. Jaha, “Deep Learning-Based Child Handwritten Arabic Character Recognition and Handwriting Discrimination,” Sensors, vol. 23, no. 15, p. 6674, 2023, doi: 10.3390/s23156774.

[12] A. M. H. Azis, and D. P. Lestari, “XGBoost and Convolutional Neural Network Classification Models on Pronunciation of *Hijaiyah* Letters According to Sanad,” JOIN: J. Online Informatika, vol. 8, no. 2, pp. 194-203, 2023, doi: 10.15575/join.v8i2.1081.

[13] I. Khandokar, Md. M. Hasan, F. Ernawan, Md. S. Islam, and M. N. Kabir, “Handwritten character recognition using convolutional neural network,” Journal of Physics Conference Series, 2021, doi: 10.1088/1742-6596/1918/4/042152.

[14] R. M. Ahmed, T. A. Rashid, P. Fattah, A. Alsadoon, N. Bacanin, S. Mirjalili, S. Vimal, and A. Chhabra, “Kurdish Handwritten Character Recognition using Deep Learning Techniques,” arXiv:2210.13734 [cs.CV], vol. 46, p. 119278, 2022, doi: 10.1016/j.gep.2022.119278.

[15] R. Wiryasaputra, “Pengklasifikasian Citra Tulisan Anak melalui Metode CNN sebagai Pendukung Pendeteksian Dini Disgrafia,” InComTech: Jurnal Telekomunikasi dan Komputer, vol. 11, no. 3, pp. 233-242, 2021, doi: 10.22441/incomtech.v11i3.13769.

[16] W. Albattah, and S. Albahli, “Intelligent Arabic Handwriting Recognition Using Different Standalone and Hybrid CNN Architectures,” Appl. Sci., vol. 12, no. 19, p. 10155, 2022, doi: 10.3390/app121910155.

[17] S. Momeni and B. BabaAli, “A Transformer-based Approach for Arabic Offline Handwritten Text Recognition,” arXiv preprint arXiv:2307.15045 [cs.CV], 2023, doi: 10.48550/arXiv.2307.15045.

[18] M. B. Bora, D. Daimary, K. Amitab, and D. Kandar, “Handwritten Character Recognition from Images using CNN ECOC,” Elsevier B.V., 2020, doi: 10.1016/j.procs.2020.03.293.

[19] L. Berriche, A. Alqahtani, and S. RekikR, “Hybrid Arabic handwritten character segmentation using CNN and graph theory algorithm,” J. King Saud Univ. - Comput. Inf. Sci., vol. 36, no. 1, p. 101872, 2024, doi: 10.1016/j.jksuci.2023.101872.

[20] D. S. Prashanth, R. V. K. Mehta, and N. Sharma, “Classification of Handwritten Devanagari Number – An analysis of Pattern Recognition Tool using Neural Network and CNN,” Elsevier B. V., 2020, doi: 10.1016/j.procs.2020.03.297.