

Integrated Convolutional Neural Network and Genetic Algorithm Based Technique for Emnist Handwritten Character Recognition

Balram Yadav, Jyoti Bala Gupta, Abhinav Shukla

Research Scholar, Dr. C.V. Raman University, Kota, Bilaspur, Chhattisgarh, India.

Dr. C.V. Raman University, Kota, Bilaspur, Chhattisgarh, India.

yadavbalram869@gmail.com, .jyotibalagupta.cvru@gmail.com

amitshukla9611@gmail.com

Abstract: *In the landscape of modern computational research, pattern recognition has emerged as a sprawling domain, offering immense opportunities for academic contribution. This field encompasses a wide variety of data modalities, including audio signals, video streams, and digital images of handwritten digits or characters. This research specifically focuses on the domain of handwritten character recognition and classification. Given the inherent variability in individual handwriting styles and the vast diversity of global languages, there is a critical need for models capable of high-precision identification. While a multitude of deep learning and traditional machine learning frameworks have been developed to address this challenge with varying degrees of success, Convolutional Neural Networks (CNNs) have recently dominated the computer vision sector due to their efficacy in real-world applications. This study introduces an integrated methodology designed to overcome the limitations of individual models and improve overall classification performance. Specifically, we propose a hybrid architecture—CNN-GA—which synergizes the global search capabilities of Genetic Algorithms (GA) with the hierarchical feature processing of Convolutional Neural Networks (CNN). In this proposed framework, the GA is employed as an optimization tool to select the most relevant features from the data, which are then processed by the CNN for final classification. To validate this approach, we utilized the extensive EMNIST dataset, a benchmark collection comprising 145,600 handwritten samples of characters A through Z. By implementing the CNN-GA model, we achieved a superior recognition accuracy of 97.98%. This performance indicates a significant advancement over previous methodologies, demonstrating that the fusion of evolutionary optimization and deep learning provides a more robust solution for complex pattern recognition tasks. The results confirm that our proposed model sets a new benchmark for accuracy in the automated interpretation of handwritten data.*

Keywords: EMNIST Handwritten Character Dataset, Convolutional Neural Network (CNN), Genetic Algorithm (GA).

I. INTRODUCTION

In the domains of machine learning and deep learning, numerous researchers have successfully implemented frameworks for diverse computer vision tasks, including pattern recognition, facial analysis, and image processing. As a specialized subfield of machine learning, deep learning architectures are uniquely capable of iteratively refining feature representations to achieve superior model accuracy. Addressing the specific challenge of handwritten character recognition, this paper introduces an integrated approach that synergizes optimization with deep learning methodologies. Specifically, a Genetic Algorithm (GA) is deployed to optimize and select the most salient features from a handwritten character dataset, which are subsequently passed to a Convolutional Neural Network (CNN) for



final classification. To rigorously evaluate the performance and accuracy of this proposed integrated model, experiments were conducted using the EMNIST handwritten character dataset. Sourced from the official National Institute of Standards and Technology (NIST) repository (<http://www.nist.gov>), this benchmark dataset comprises a comprehensive collection of 145,600 samples, providing a robust foundation for verifying the model's classification efficacy.

The Extended MNIST (EMNIST) database is fundamentally derived from the NIST Special Database 19 [1], a comprehensive repository of training materials for character recognition containing over 800,000 manually verified samples. Recent scholarship [2] has explored various methodologies across MNIST and EMNIST, highlighting that while deep learning—specifically Convolutional Neural Networks (CNNs)—remains the standard for image classification, alternative preprocessing like SVD-based dimensionality reduction has shown competitive results. Advanced architectures, such as deep neural networks integrated with encoders, have successfully achieved recognition rates as high as 98.5% on testing samples [3], while Deep-CNN implementations have further validated performance by analyzing accuracy relative to the number of training iterations [4]. Innovative neuroevolutionary approaches have also emerged; for instance, the use of neuroevolved CNN committees and topology transfer learning has yielded high precision on EMNIST Letters and Digits subsets [5]. Similarly, Evolutionary-DNN techniques have achieved up to 99.3% accuracy for handwritten digits [6], while refinements to the classic LeNet model have pushed balanced recognition rates to 99.50% [7]. Hybrid strategies involving feature extraction via Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) combined with Support Vector Machines (SVM) have also been effective, with SVM consistently outperforming K-NN, reaching 97.74% on EMNIST Digits [8]. Hierarchical classifiers, which automatically analyze confusion matrices to refine classification, have reported accuracies of 99.46% for Digits and 93.63% for Letters, though "flat" CNN settings often still perform optimally [9]. Additionally, neuroevolutionary models like EDEN have established benchmarks of 88.3% on EMNIST Balanced and 99.3% on EMNIST Digits [10]. In alignment with these advancements, our study employs a CNN as a primary feature extractor, subsequently utilizing SVM, K-NN, Random Forest, and XGBoost for classification to establish a comparative performance baseline against these existing models. Author [11] proposed a customized hybrid framework combining deep learning and machine learning for EMNIST handwritten character recognition. Published in IJARSCT, their study addresses the challenge of recognizing highly variable handwriting styles. By integrating these paradigms, the authors optimized feature extraction and classification processes. Ultimately, their hybrid model demonstrated enhanced recognition accuracy over traditional standalone methodologies. Author [12] presented a comparative analysis of MLP, CNN, and Residual CNN models for handwritten character recognition using the EMNIST dataset. The study concluded that Residual CNN achieved better recognition accuracy than traditional CNN and MLP models. The research also highlighted the importance of optimization techniques and hyperparameter tuning for improving classification performance. Author [13] introduced an extended EMNIST evaluation dataset to support advanced handwritten character recognition research. Their work provided additional handwritten samples and benchmarking features for evaluating machine learning and deep learning models. The proposed dataset offered improved opportunities for analyzing OCR and handwritten recognition systems. Now the author [14] proposed a Sobel-gradient based MLP approach for handwritten character recognition using EMNIST Letters and MNIST datasets. The method utilized edge-based feature extraction instead of convolutional operations and achieved nearly 92% classification accuracy. The study demonstrated that gradient-based preprocessing techniques can significantly improve recognition efficiency and model performance. Author [15] conducted a comparative study of CNN, LSTM, Transformer, and MLP models for handwritten text recognition tasks. Experimental results showed that CNN-based architectures achieved the highest recognition accuracy and lower error rates on benchmark datasets. The authors recommended deep CNN models for reliable and efficient OCR applications. An author [16] investigated several deep CNN architectures such as VGG16, DenseNet201, MobileNetV2, and InceptionResNetV2 for handwritten character recognition. Their experiments revealed that InceptionResNetV2 combined with data augmentation provided superior recognition performance compared to other architectures. The research emphasized the importance of deep feature extraction and augmentation techniques in



improving recognition accuracy. Author [17] reviewed recent CNN-based handwritten digit recognition approaches using MNIST and EMNIST datasets. The study observed that advanced CNN models consistently achieved good recognition accuracy on benchmark datasets. The authors also discussed the significance of data augmentation and deep learning optimization techniques for improving OCR systems and handwritten character recognition performance.

In this paper, we enhance the recognition accuracy of tetsing dataset by our proposed integrated models, which is combination of genetic algorithm and convolutional neural network CNN-GA. Our proposed hybrid models CNN-GA achieved higher recognition rate with EMNIST dataset, that proves the performance of our proposed model are excellent and provide better result.

II. PROPOSED ARCHITECTURE

In this section, we have explored the proposed architecture and their description of research work. The proposed integrated Technique for handwritten characters recognition consist two steps ,where first step is feature optimization using genetic algorithm and second step is classifying the optimized features using convolutional neural network. We have implemented the proposed integrated model CNN-GA with EMNIST handwritten character dataset. Here we have represents the model architecture and description.

Proposed Architecture - The model architecture has been represented in figure-1.

Proposed Architecture description – This model contains three step for implementation :-

- Data Collection & Preprocessing
- Optimization by Genetic Algorithm
- Classification & Recognition using Convolutional Neural Network

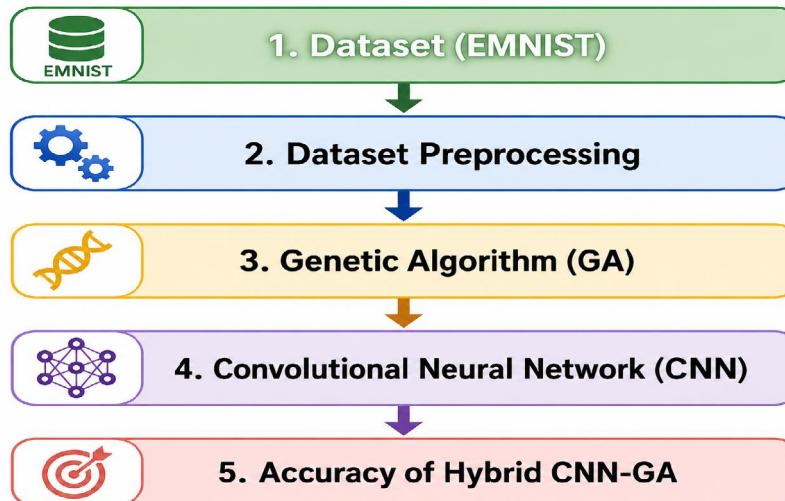


FIGURE I. Flow diagram of proposed hybrid CNN-GA model

Data Collection & Preprocessing

For handwritten character recognition, we have downloaded the dataset Extended Modified National Institute of Standards and Technology database (EMNIST) form https://www.itl.nist.gov/iaui/vip/cs_links/EMNIST/gzip.zip. The dataset EMNIST is a collection of 145600 samples, which is divided into four files, 1st for 124800 image sample used as training images, 2nd for 124800 labels of training samples, 3rd for 20800 image sample used as testing images and 4th for 20800 labels of testing samples. For implementation on model, dataset needs preprocessing, for that first normalize the data images and then reshape it as 28*28 dimensions. The sample of the images of data represented by figure -2 and total number of training and testing samples of each digit represents in figure-3.





FIGURE II. SAMPLE OF EMNIST TRAINING DATASET IMAGE

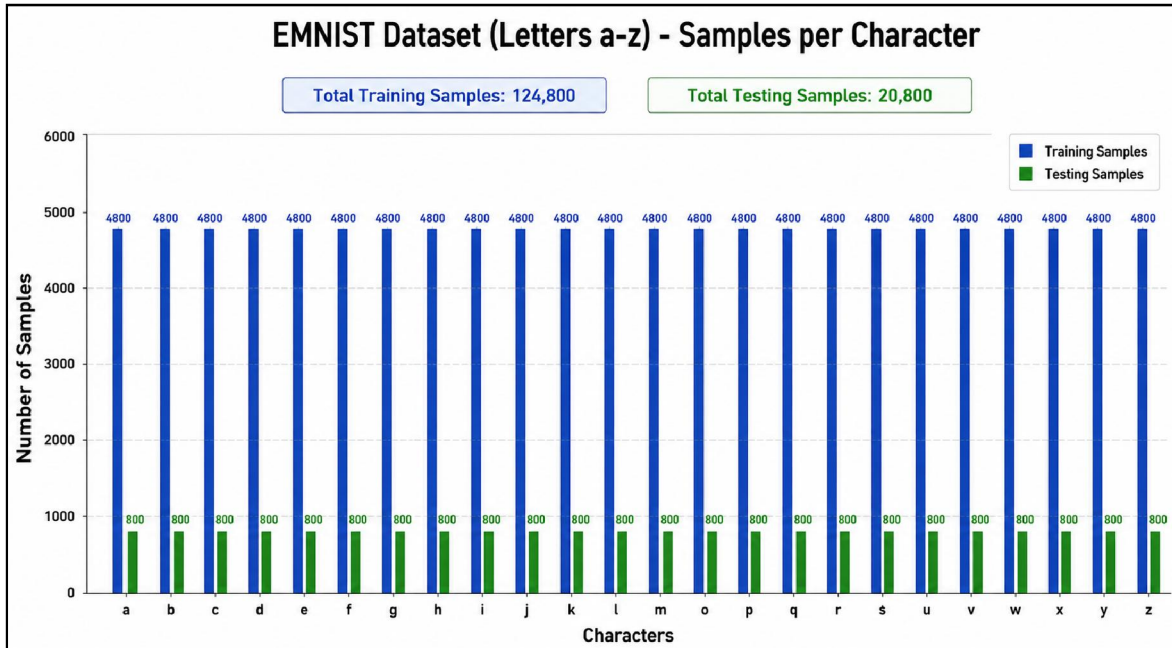


FIGURE III. TRAINING AND TESTING SAMPLES OF EACH CHARACTERS (A – Z)

Optimization by Genetic Algorithm

The operational workflow of the genetic algorithm is outlined in the following sequential steps:

Initially, a randomized initial population is generated.

Subsequently, the algorithm iteratively develops a series of successive populations. At each step, individuals from the current generation are leveraged to construct the next population through the following procedures:

Determines the fitness value of each individual within the current population to evaluate their performance.

Scales the raw fitness scores to map them into a standardized range of values for enhanced usability.

Selects candidate members, designated as parents, based on their relative fitness scores.

Designates elite status to the highest-performing members of the current population, directly passing these elite individuals to the subsequent generation.

Generates offspring from the selected parents. Offspring are produced either by randomly altering a single parent via mutation or by combining the vector entries of two parents through crossover.

Integrates the newly generated offspring into the population to form the next generation.

The algorithm terminates when one or more predefined convergence or stopping criteria are satisfied.

The foundational terminology utilized within the genetic algorithm is defined as follows:

Individual—The distinct candidate solution that attempts to resolve the optimization problem.

Genes—The set of characteristics or parameters that define a specific individual. Examples include a sequence of strings or, in the context of this study, the weight parameters of the neural network.

Population—A collective group of individuals working simultaneously to optimize the target problem.

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Generation—The entire state of the population at a specific iteration. Each subsequent generation ideally exhibits superior performance compared to its predecessor, with members either derived from the previous generation or randomly generated.

Elitism—The process by which the top-performing individuals of the current generation are immediately propagated to the next generation to preserve high-quality solutions.

Mutation—A mechanism where highly fit individuals are selected from the current population, and minor, random alterations are introduced into their genetic structures to generate a novel candidate solution.

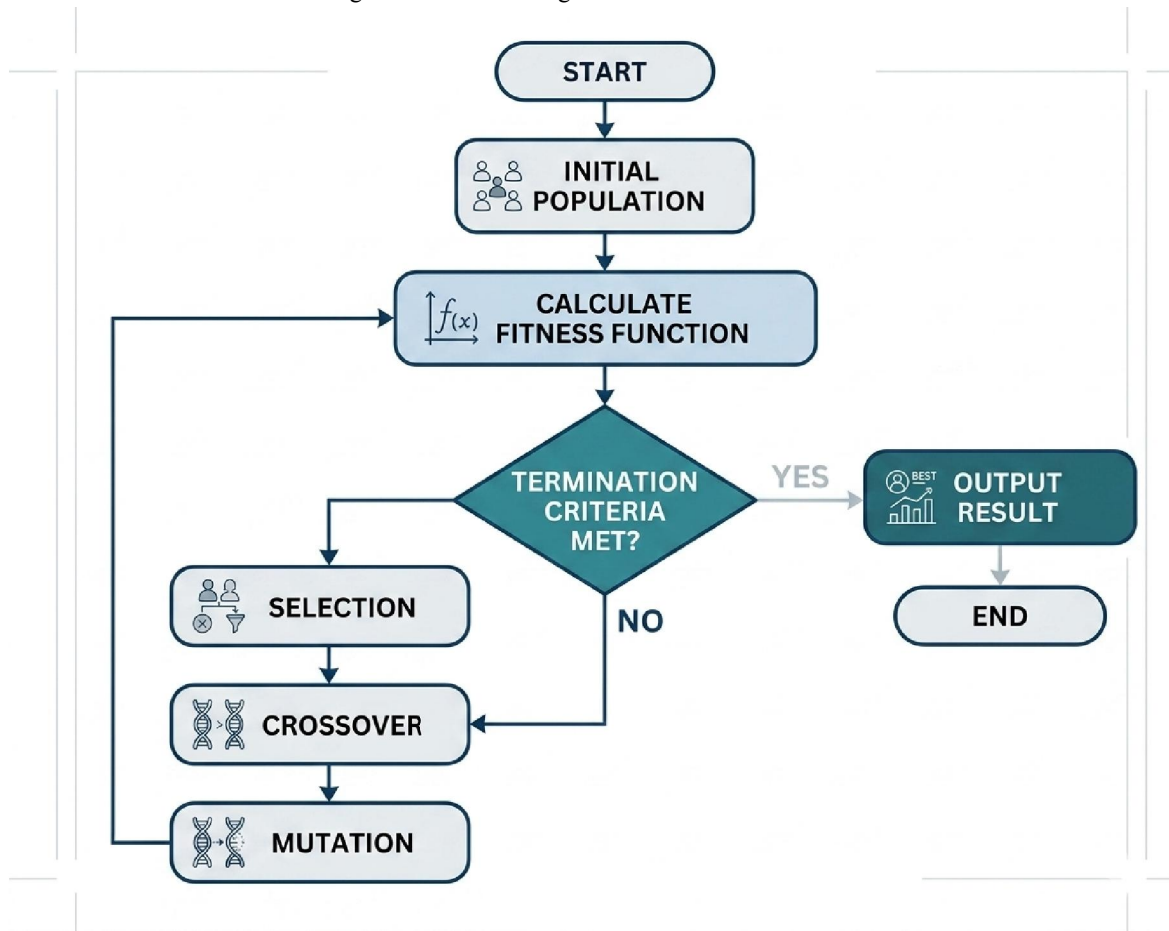


FIGURE Iv. Flow diagram of Genetic Algorithm

Classification & Recognition using Convolutional Neural Network

The customized convolutional neural network is used for recognition and classification. The proposed architecture of CNN is represented below.

Stage 1: The pipeline begins with the network input stage (input_layer_3), which directly feeds into initial convolutional layers conv2d_24 and conv2d_25 to capture low-level spatial characteristics. Spatial dimensions are down sampled using max_pooling2d_6 before stabilization through batch_normalization_15.

Stage 2: Intermediate feature learning is executed by a sequence of processing layers: conv2d_26, batch_normalization_16, conv2d_27, and batch_normalization_17. The network then scales up to deeper feature spaces using a cluster of 64-filter convolutional layers, namely conv2d_28, conv2d_29, and conv2d_30.



Stage 3: Final down sampling is performed by `max_pooling2d_7`, followed by regularization at `batch_normalization_18`, a localized feature refinement step through `conv2d_31`, and a final normalization layer at `batch_normalization_19`. The multidimensional feature maps are collapsed into a single vector via `flatten_3` before moving through a dense hidden network topology (`dense`) to output the final prediction vector (`dense_1`).

III. EXPERIMENTAL APPROACH

The implementation of the proposed architecture was executed within an Anaconda Navigator (Anaconda3) environment utilizing the Python programming language, with TensorFlow and Keras serving as the primary deep learning libraries. The proposed integrated framework, designated as CNN-GA, is structured into two distinct, sequential phases: a feature optimization stage driven by a Genetic Algorithm (GA), followed by a classification stage handled by a customized Convolutional Neural Network (CNN). Prior to the optimization and training phases, the EMNIST handwritten character dataset underwent strict preprocessing. The raw pixel values of the image samples were normalized by dividing each pixel by 255, mapping the feature space to a standardized range between 0 and 1. Subsequently, the data samples were reshaped into a consistent structure of 28×28 pixels, yielding a 784-dimensional vector for each input image.

The feature optimization process was managed by tuning specific hyperparameters within the Genetic Algorithm. The foundational configuration for the GA execution included an initial population size of 30, a mutation rate of 0.1, and a crossover rate of 0.2. The evolutionary process was bound by a maximum threshold of 100 iterations, with a target minimum fitness value established at 0.95. Furthermore, the mating pool size was set to 8, the elite number parameter was defined as 4 to preserve top-performing solutions, and a batch size of 1,000 samples was maintained. Hyperparameter tuning was iteratively performed across these variables to analyze variation in the system's performance.

The optimized feature subsets produced by the GA were ultimately fed into the customized CNN model, which utilized the Adam optimizer for weight adjustments during training. When benchmarked against the EMNIST dataset, the proposed hybrid CNN-GA model yielded an exceptional empirical testing accuracy of 97.98%, demonstrating superior classification performance over existing historical baselines.

IV. RESULT ANALYSIS

Comparison of Proposed Integrated model with previous research work: -

In the field of handwritten character recognition, various authors contributed their research experience by using convolutional neural network technique and Hybrid techniques of machine learning and deep learning. In this paper, we have proposed integrated model based on genetic algorithm with deep learning, and we achieved excellent result with this proposed model. The comparative analysis of various framework of CNN and Hybrid model represented in Table-I.

TABLE I. COMPARISON OF ACCURACY OF VARIOUS MODELS

Reference	Name of the Model	Validation Accuracy
[8]	DWT-DCT + SVM	89.51%
[9]	CNN (flat; 2 conv + 1 dense)	93.63%
[10]	EDEN	88.30%
[11]	Previous Proposed Hybrid CNN-RFC	87.95%



[11]	Previous Proposed Hybrid CNN-KNN	93.39%
[11]	Previous Proposed Hybrid CNN-SVM	94.99%
[11]	Previous Proposed Hybrid CNN-XGB	96.01%
[13]	WaveMixLite	95.69%
[13]	VGG-5	95.87%
[14]	MLP	92%
	Integrated CNN-GA	97.98%

V. CONCLUSION

In the area of pattern recognition, the domain of handwritten character recognition has been adopted by various authors. In this paper we have proposed integrated hybrid model for recognition of EMNIST handwritten character dataset. The hybrid model is combination of optimization technique and deep learning approach. GA is a optimization algorithm used for optimizing features and CNN is the part of the deep learning used for classification. From the implementation of proposed ingrated model, we achieved 97.98% recognition accuracy with EMNIST character dataset which represents the excellent performance of model.

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