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A NOVEL CUTTING EDGE NATURE INSPIRED OPTIMIZATION OF BRAHMI CHARACTERS RECOGNITION

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Abstract

Feature extraction techniques and classification tools have been used in Optical Character Recognition for many years. Machine learning models and Convolutional Neural Networks (CNN) have been proven more effective in handwritten character recognition. Optimizing the hyperparameters of machine learning models is still a challenging task. Hence, this work accomplishes Brahmi character recognition by using a convolutional neural network and random forest classifier where hyperparameter tuning of the machine learning model has been improved using a genetic algorithm. The characteristics from the images of Brahmi letters are extracted using a CNN-based autoencoder fed to the random forest classifier. The suggested Algorithm's performance is compared to other existing algorithms using performance parameters. It achieves an accuracy of 97% which is much better than the 92% or 94% accuracy achieved by CNN-only or CNN-based random forest.

Keywords: *Brahmi Script, Inscriptions, CNN, Epigraphy, Random Forest, GA*

1. Introduction

Researchers have been interested in handwritten letters and numerals identification for over five decades. It is regarded as a difficult issue due to its potential applications in a variety of fields. Much work has been done on handwritten character identification in Indian scripts, which was previously ignored. Pattern recognition refers to a more general category; character recognition is a subset of that category [1]. When doing pattern recognition, the object to be identified may be any of the universal items. But in character recognition, the focus is on the text, a combination of alphabets and numerals.

It may need to be more to identify items in a picture or a video sequence and then track the movement of a single object over time for specific applications. It may be required in some circumstances to identify a particular item in a scene. Pattern recognition is one approach that may be used to accomplish this [2]. It is also being used in the manufacturing industries with the aim of quality control. For instance, an image analysis system monitors newly machined screws as they pass before a camera while moving on a conveyor belt. The digital representation of each screw is rotated until it is in perfect alignment with the picture that was previously saved of a flawless screw [3]. When a change due to a fault in the screw is discovered compared to the saved

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image, that screw is eliminated from the list of passing items and put in the damaged category. The process of automatically recognizing faces also makes use of pattern recognition. Identifying individuals in a group of moving people is possible, provided their photos have been saved already using this method.

One subset of pattern recognition is known as optical character recognition, and it requires the program to recognize the written character from its picture and then save it as the digital counterpart in the form of an ASCII code. The fact that a character may be represented in various sizes, fonts, and styles, such as italics and boldface, makes this process challenging.

Text recognition is another name for optical character recognition (OCR), which stands for optical character reading. The data from scanned papers, camera photos, and OCR software may be used to extract text. Individual letters are extracted from an image using an optical character recognition (OCR) tool, automatically allowing access and change to the original material and increasing speed. In addition to this, it removes the need for manually entering data. OCR systems use a mix of hardware and software [4] to transform hardcopy documents into text readable by a computer. Specialized hardware, such as an optical scanner or a printed circuit board, copy or read text. At the same time, the software usually is responsible for handling the more complex processing steps.

OCR software may use artificial intelligence (AI) to perform more sophisticated OCR approaches, including discriminating between languages or handwriting styles[5]. Different machine-learning techniques are used for this purpose. OCR allows consumers and organizations to keep data on their personal computers, laptops, and other electronic devices, guaranteeing that all paperwork will always be accessible [6].

The following is a list of advantages that may be gained by using OCR technology:

a. Cost reduction.
b. Increase in the speed.
c. Automation of documents and processing of content.
d. Centralize the safeguarded data.
e. Enhance the quality of service by ensuring that all personnel has access to the most recent and precise information.

CNN has lately been one of the most attractive methodologies and has played a significant role in some recently effective and demanding applications concerned with machine learning like object identification, image categorization, face recognition etc. Picture recognition is used in various processes, including automatic image organizing, stock photography, and more [7].

CNN is a deep artificial neural network for object detection, photography and categorization. It is capable of recognizing a wide variety of universal visual data available. CNN's most crucial structural component is called the convolutional layer. The layer's parameters are built up of kernels or filters. These filters have a narrow receptive field, yet their range extends to the whole

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volume of the input. A two-dimensional activation map of each filter is created during a forward pass by convolution of the width and the height of the input volume [8]. The dot product is calculated and mapped out using this method, as shown in Figure 1. Thus, the network learns more about its filters due to these actions. Operators activate the filter when they see a specific feature type at a particular point in the input.

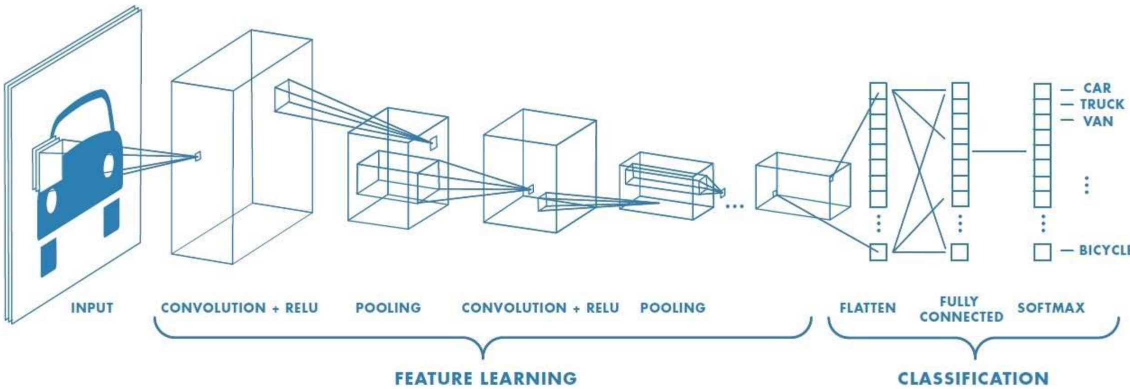

FIGURE 1: **IMAGE CLASSIFICATION USING CNN [9]**

A down-sampling layer follows; the activation patterns are supplied one patch at a time to that layer. One label is assigned to each node in a CNN's fully linked output classification layer.

In this article, a Brahmi character identification is made using a revolutionary genetic algorithm based on a Random Forest classification method [10-11]. Features collected from images are supplied to an autoencoder in a convolutional neural network for image categorization. A genetic method is used to improve hyperparameter tweaking. Accuracy, sensitivity, specificity, and the F1 score are considered to gauge the Algorithm's effectiveness and performance metrics[12].

Furthermore, the article is structured so that sections-2 discusses the literature review, section 3 discusses the methodology used, section 4 illustrates the findings, and section 5 ends the study after giving conclusions and future work.

2. Literature Review

Katsouros et al. 2016 said that studying ancient scripts using modern computer technologies is known as computational epigraphy. Previously, reading, understanding, and analyzing each letter of the ancient text, which was necessary for the decipherment process, was done manually [13]. Computational epigraphy automates the otherwise laborious task of manually studying the character.

Rajan et al. 2017 research on the statistical analysis of written language from the ancient Brahmi script to contemporary Tamil analysis of the syntactical structure of utilization of vowels and consonants is 44% and 56%, respectively [14]. Although the Brahmi script is the oldest, the language is fully formed. Brahmi Script results from a long, complex evolution of writing systems dating back to the earliest. Rao et al. 2009 used the Markov Chain model to capture sequential

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dependencies between signs in the Indus script. New text is generated and analyzed after training on the Indus seals found in Mesopotamia and Western Asia. Missing/ ambiguous characters can also be guessed using that model [15].

Chanda et al. 2009 stated that the Brahmi script contains 207 characters, including 9 vowels, 18 consonants, and 180 vowel-consonant combinations. The author has done a remarkable job of reinterpreting the carvings [16].

Raj et al. 2017 stated that the Brahmi script is the oldest known inscription, and it has a complex syntactic structure that draws on palaeography, orthography, and linguistics [17]. Records show that this script is the ancestor of all Indic scripts. Gupta et al. 2022 said that in South India, the Brahmi period marks the beginning of the Early Historic era, and in Southeast Asia, where there is a wealth of ancient literature, etching is the primary source of crucial material. Many ancient works, like the Tholkapiyam and the Thirukural, were written using this script [18]. The Brahmi text begins the Early Historic period in South India. The engravings are the primary source of essential data with a wealth of ancient writing in Southeast Asia, which inform about the civilization, knowledge, commerce, religion, economics, linguistics, lords etc. These engravings are useful for an investigation of 5,000-year-old authentic events. Roy et al. 2016 studied ancient images of inscriptions and found that images contain text which was Brahmi inscriptions [19]. Sahlol et al. 2020 found a picture of an Indian imitation of European rouletted ware bearing Alagankulam, Ramanathapuram District.

However, no calculation has been developed for the Brahmi script; this fact inspired the development of a framework for transcribing the Brahmi script [20-22]. This study has the potential to persuade historians, linguists, and other scholars to use primary sources to advance the field of computational linguistics. Deciphering entails painstakingly locating each letter in the engraving and reading its abstract message.

This investigation is based on the most direct engravings, known as "Brahmi," "Damili," and "Dravidi," which may be found in Jaina and Buddhist works and may correspond to different stages of the content from which all other local contents (apart from Indus content) were extrapolated. India's languages, literature, philosophies, religions, and scripts excited the British. William Jo of Calicut established the "Asiatic Society" in 1784 to study scripts. James Prinsep gave this writing system the name "Brahmi" in 1837. Dr Iravatham Mahadevan, an eponymous epigraphist, has decoded a text written in Brahmi [23].

2.1 Script Recognition

Caggiano et al. 2019 have been devoted to script recognition for over 30 years. With the recent development of computer tools, a quantitative examination of script recognition is performed [24]. Han et al. 2020 accepted the challenges and designed multiple methods (support vector machines, principal component analysis, convolutional neural networks, recurrent neural networks, and Markov models).

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2.2 Mathematical Structure Models

Awel et al. 2019 found a substantial element of compromise in mathematical modelling. Although mathematics may be used to show broad generalizations, the precise nature of such inferences is inextricably bound up with the specific form of the equations used. Yu et al. 2020 found a seemingly slight adjustment to the presentation of the equations and may need a significant reworking of the underlying mathematics [25]. Computer-enabled quantitative measurements have to be made.

2.3 Machine Learning

Standard machine learning algorithms that create a model from training data follow the well-known inductive approach. The model is created using the learned data and machine learning analytical framework. Wei et al. 2018 stated that the technology is used for many applications, including language and audio processing, script recognition, and more [26]. However, the generalization of a model determines the usefulness and effectiveness of machine learning. Preventing performance deterioration between the actual input and training data requires sufficient impartial training data. Li et al. 2019 stated that when a model is overfitted to its training data, it produces subpar results on new data even if it did well on the old one.

2.4 Artificial Neural Networks

An artificial neural network (ANN) is the first kind of artificial intelligence which mimic the human interpretation of text and pictures to build its model. Jian et al. 2018 found that in the training phase, the data-collecting stage compiles relevant information about the network solution; this knowledge is then used in the analysis phase during decision-making. The neural network of living organisms, namely humans, is a primary inspiration for ANN. Aggarwal et al. 2015 stated that the essential ANN makes possible the computer systems to be intelligent by providing the machine with sufficient learning [27].

2.5 Deep Structured Learning

Aziz et al. 2011 used Deep learning, which feeds raw data into the training algorithm without extracting features or providing a feature specification matrix. Higher-level layers combine edges and curves to pave the way for more abstract "object pieces" to be created in the subsequent layer. This process may be considered hierarchical learning since each successive layer builds upon the information the lower layers provide. Cho et al. 1995 stated that the output layer is responsible for classifying the script and getting the output class label [28].

2.6 Research Gaps

Kannan et al. 2015 stated that the absence of a representative corpus is the primary gap in the investigation. Users without experience tweaking CNN architectures may utilize CNN-GA to find the optimal architecture for solving image classification challenges. Two rigorous

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benchmark datasets were used to evaluate the proposed technique, and it was compared to 18 state-of-the-art peers. According to the findings of the experiments, CNN-GA has better classification accuracy than both automatically constructed CNNs and their peers and is competitive with automated and manually tuned peers [29]. However, the amount still needs to be increased compared to GA's usage of computing resources for solving classical problems.

3. Methodology

We have broken down the planned CNN into five main sections to explain our suggested goal further. Data training involves sending images through many layers before reaching a max-pooling layer. A softmax activation function adds to the output through the last layer before sending it. This method has wide-ranging potential applications, including face recognition, security, and more. It requires segmenting the picture, extracting relevant characteristics, and then classifying the image based on those features [30].

Learning to recognize Brahmi writing, a script written in ancient India, is one of the most advanced forms of machine learning. Data collection, pre-processing, data extraction, data selection, and script validation are all crucial steps in creating a standardized corpus of untranslated Brahmi scripts, which is the starting point for computational epigraphy. This project aims to use a dataset to train a Convolution Neural Network to recognize Brahmi writing, a script written in ancient India.

3.1 Design of Experiments

This study's primary focus is on learning how to recognize Brahmi script characters:

- Data collection, pre-processing, data extraction, data selection, and script validation are all crucial steps in creating a standardized corpus of untranslated Brahmi scripts, which is the starting point for computational epigraphy.
- This project aims to use a dataset to train a Convolution Neural Network to recognize Brahmi writing, a script written in ancient India.
- Try the transfer learning technique by optimizing a Brahmi-specific pre-trained network with a depth-wise separable convolutional network, and see how it works.
- To create a transliteration framework, utilizing Brahmi as the original language and another readable language as the target.

The Brahmi letter dataset will be classified via a random forest classifier. Dataset characteristics are extracted using the convolutional auto-encoder, and the reconstructed picture is identified using a random forest classifier after the machine learning model's hyperparameters have been adjusted using a genetic algorithm[32-33]. It will be compared to similar algorithms using standard performance metrics to demonstrate its effectiveness.

3.2 Data Collection

The Brahmi letter dataset was used to test the effectiveness of the proposed method is:

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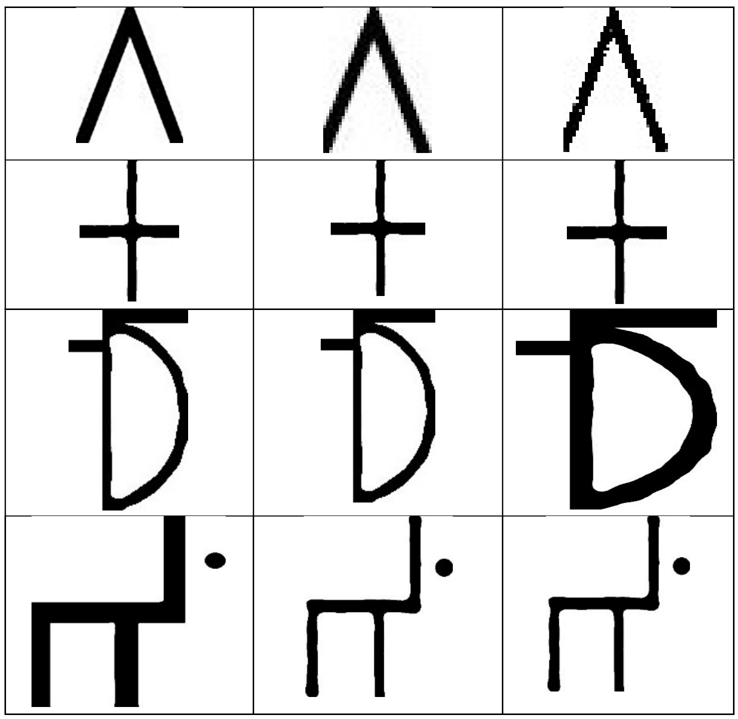
https://www.kaggle.com/datasets/gautamneha/brahmi-dataset

The Brahmi dataset contains a wide range of sample characters. This set has 170 characters, including 27 other consonant classes, four vowel classes, and 139 compound character classes. The database includes 6,475 picture representations of Brahmi words, divided into 170 classes, and 536 character representations of these words, also divided into 170 classes, for use in the training process. This collection also includes Brahmi text samples for testing segmentation methods [34]. The sample of the dataset is shown in Table 1.

Table 1: Sample of the dataset



3.3 Data Pre-processing

The data undergoes many pre-processing phases to improve the fit before being included in the model. Initially, the multiple-letter pictures in each folder were of varied sizes, so all images were scaled to 64x64 pixels. The model makes incorrect classifications because some of the photographs in the folders are blurry. The photos are deblurred to prevent this from happening.

In contrast to the colour photos in the dataset, the images in the dataset are grayscale. Images in RGB format are required for the convolutional neural network technique to function correctly. That is why they go to the trouble of colourizing the grayscale photos.

3.4 Data Analysis

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The output layer of a convolutional auto-encoder is a trained neural network replica of the input layer's image. A Tan encoder called ConvNet is used. The decoder is another illustration of a ConvNet at work, and its job is to restore the original picture from its compressed counterpart to reduce the number of dimensions necessary to describe an image. Data is compressed by the encoder and then restored by the decoder. Because of this, autoencoders may be used to reduce file sizes without sacrificing quality. Instead of using standard compression techniques like JPEG and MP3, data-specific compression logic is learned from the data. Autoencoders also have applications in image denoising, dimensionality reduction, and image search. Figure 2 depicts the application of a convolutional autoencoder.

Figure 2: Procedure of Convolutional AutoencoderEncoder

3.5 Algorithm

```
Genetic Algorithm for hyperparameter tuning
Populations ← m models list with different hyperparameters
Generation ← 0;
While
        Generation < max generation
do
        train_and_evaluate (population);
        new_generation ← retaining the n fittest individuals;
        new_generation ← append random individuals to promote diversity;
        mutate (new_ generation)
        new_generation ← append offsprings through crossover until p;
        population ←, new _ generation
        generation ← generation + 1
end
```

Finding the optimal or most efficient solution to the problem at hand is the primary purpose of the Genetic Algorithm, which works on the assumption that mutations are rare and unpredictable. The population used in this method is a set of models with varying hyperparameter values. Since we aim to change the hyperparameter on the ML model in this scenario, above is the pseudocode for the evolutionary method used to fine-tune hyperparameters.

3.6 Random Forest

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Random Forest is a popular machine-learning approach that uses supervised learning techniques. In machine learning, it may be used for both regression and classification. To address this challenge and boost the model's accuracy, we use an ensemble learning strategy in

which many classifiers are combined? Random Forest takes many decision trees, each trained on a different subset of the dataset, to increase the accuracy of the predicted values. The random forest considers the predictions of several decision trees rather than just one, arriving at an overall prediction based on the majority's vote. This research uses a random forest method to classify Brahmi letters. Figure 3 depicts the steps of the suggested methodology.

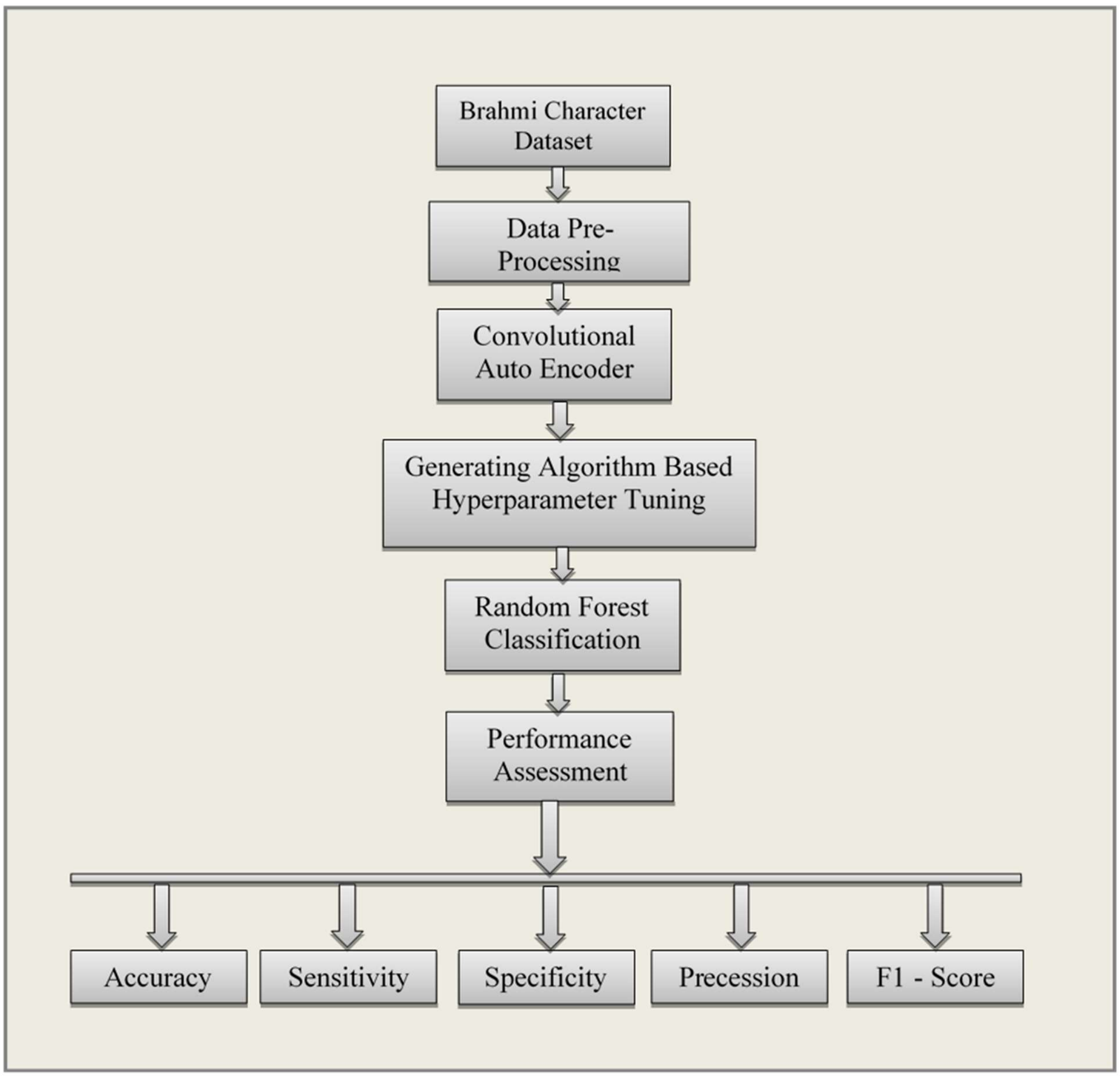

Figure 3: Methodology

3.7 Demographics

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Measures such as accuracy, sensitivity, precision, and F1-score, are used to assess an algorithm's performance in terms of the confusion matrix's performance.

Accuracy: The fraction of correctly recognized subjects to the total number of issues, as shown in equation 1.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Sensitivity: Recall, also known as sensitivity, is the proportion of correctly positive labels recognized by our computer subjects, as shown in equation 2.

$$Sensitivity = \frac{TP}{TP+FN} \quad \mathbf{(2)}$$

Precision: It is possible to calculate the precision of an outlook by considering the total number of accurate forecasts. Predictive value is another title for this concept subject, as shown in Equation 3.

$$Precision = \frac{TP}{TP+FP} \quad \mathbf{(3)}$$

F1-Score: The F1-score is a statistic that considers both accuracy and recall subjects, as shown in equation 4.

$$F1 - score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

Specificity: The system has appropriately classified the negative as specificity subjects, as shown in equation 5.

$$Specificity = \frac{TN}{TN+FP} \quad (5)$$

WHERE,
TP= TRUE POSITIVE
TN= TRUE NEGATIVE
FP= FALSE POSITIVE
FN= FALSE NEGATIVE

4. Results

In this part, we showcase the algorithms' graphical representations. CNN and CNN auto-encoder-based random forests are developed and compared to the proposed technique, CNN auto encoder-based Random Forest with hyper-parameter tuning using a genetic approach.

Table 2 shows the dataset of all the parameters for analysis. It includes the values of CNN-based Random Forest using a Genetic Algorithm.

Table 2: CNN-based Random Forest using Genetic Algorithm

Parameters	Convolutional Neural Network (CNN)	CNN autoencoder-based Random Forest	CNN autoencoder-based Random Forest with hyperparameter tuning using genetic Algorithm
Accuracy	0.92	0.94	0.97

Sensitivity	0.94	0.87	0.91
Specificity	0.84	0.92	0.89
Precision	0.87	0.82	0.94
F1-score	0.88	0.84	0.85

4.1 Analysis

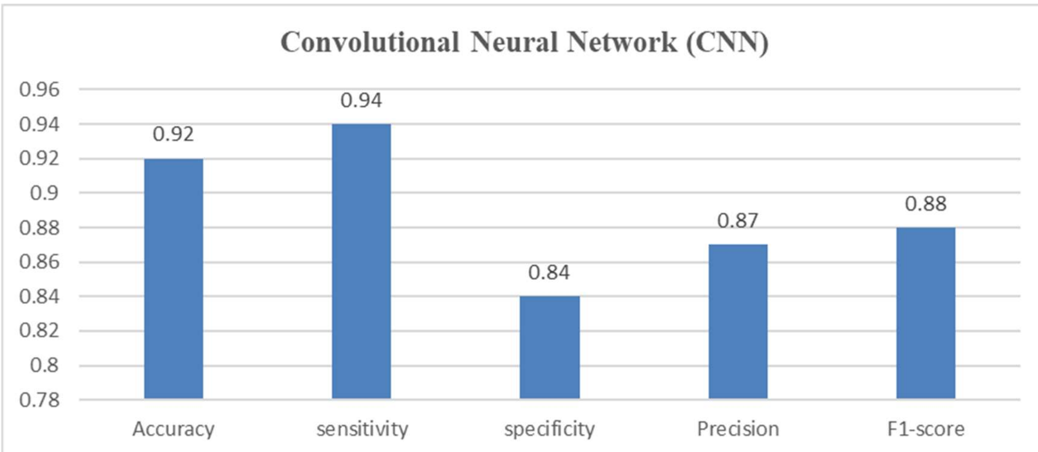

Figure 4: Performance parameters of CNN

Figure 4 depicts the performance parameters of a convolutional neural network. The Algorithm's accuracy is 0.92, i.e. 92%, sensitivity is 0.94, specificity is 0.84, precision is 0.87, and the F1-score of the Algorithm is 0.88.

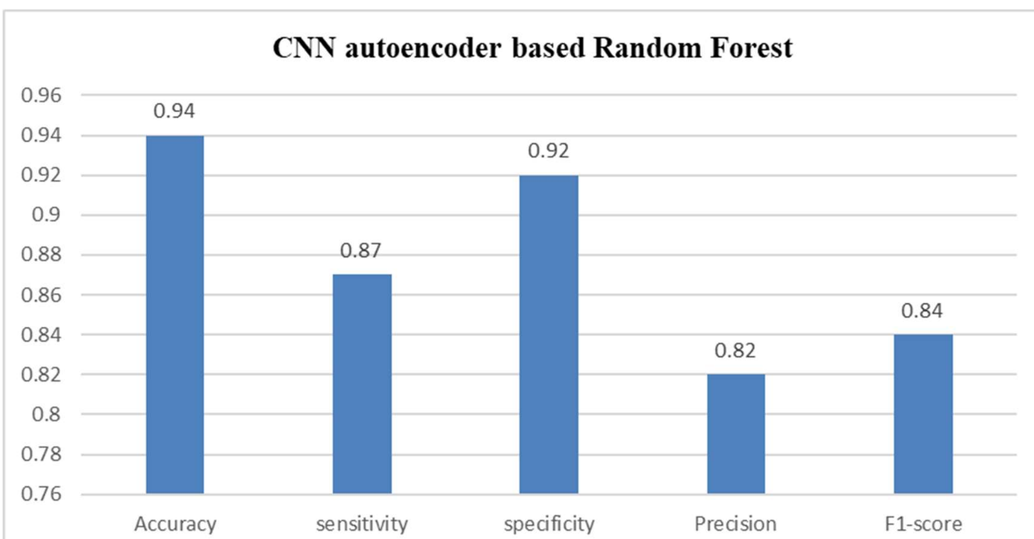

Figure 5: Performance parameters of CNN Autoencoder based on Random Forest

Figure 5 visualizes the performance parameters of a convolutional neural network auto-encoder-based random forest. The Algorithm's accuracy is 0.94, i.e. 94%, sensitivity is 0.87, specificity is

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0.92, precision is 0.82, and the F1-score of the Algorithm is 0.84.

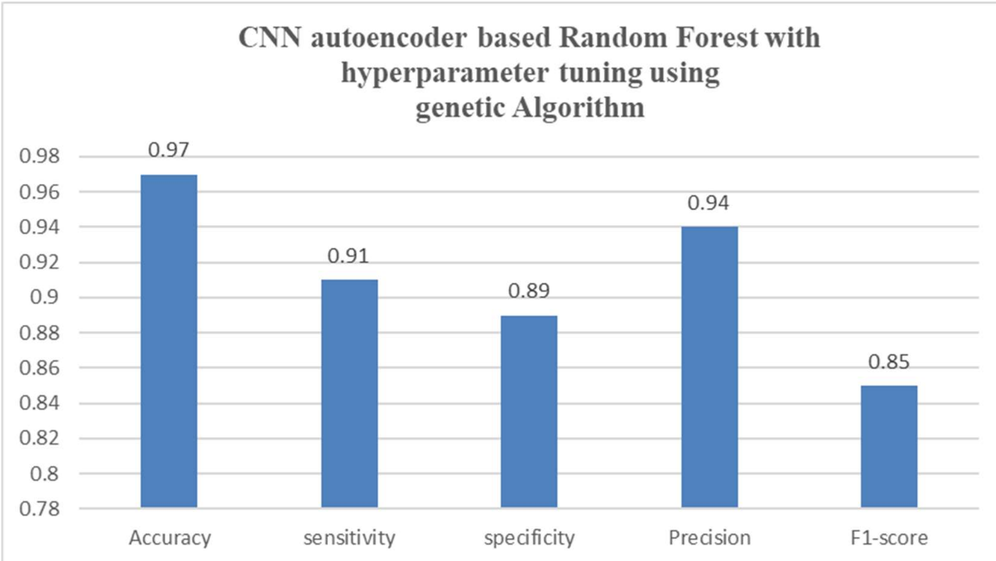

Figure 6: Performance parameters of CNN autoencoder based on Random Forest with hyperparameter tuning using Genetic Algorithm

Figure 6 depicts a convolutional neural network auto-encoder-based random forest performance parameters with hyperparameter tuning using a genetic algorithm. The Algorithm's accuracy is 0.97, i.e. 97%, sensitivity is 0.91, specificity is 0.89, precision is 0.94, and the F1-score of the Algorithm is 0.85.

4.2 Comparative Analysis

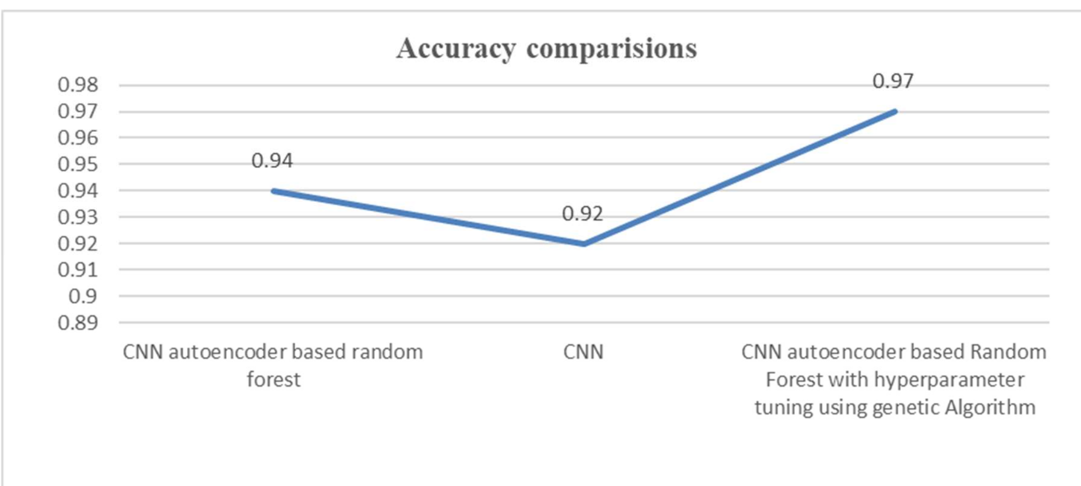

Figure 7: Analysis Comparison

Figure 7 states the analysis for a comparison of the accuracies of the proposed and existing

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algorithms. The proposed Algorithm is highly accurate compared to the other two existing algorithms.

4.3 Discussion

This paper suggests a novel network model for hyperspectral picture categorization. Using the given HSI, the 2D CNN portion extracts rich spectral-spatial properties. Subsequently, the 3D block principally deals with reconstructing the advanced spectral feature with neighbour band information incorporated in it. It is a vital step in the CNN network's feature-refining process for HSIC. One of our subsequent studies will concentrate on designing band selection and augmentation networks to extract contextual information hierarchically.

4.4 Managerial implications

A genetic method is utilized to improve the hyperparameter tweaking of this machine-learning model. The performance of the proposed method is compared to that of several preexisting algorithms like convolutional neural networks and convolutional neural network auto encoder-based random forest, using metrics like accuracy, sensitivity, specificity, precision, and f1-score.

5. Conclusion

This study uses a random forest classifier to decipher handwritten characters of the Brahmi Script. The images of the alphabet of the Brahmi language, extracted from a dataset available online, are used for various pre-processing tasks. These include picture scaling, deblurring, and conversion from grayscale to RGB. Images of Brahmi script are fed into a random forest classifier after retrieving their defining features by a CNN-based autoencoder. A genetic algorithm is used to optimize the hyperparameter tuning. The proposed method achieves 97% accuracy, whereas the state-of-the-art alternatives, CNN and CNN auto encoder-based random forest, achieve 92% and 94% accuracy, respectively. Thus, it may be deducted that the proposed method accurately identifies Brahmi characters.

5.1 Limitations

The model needs more training data to perform beyond its current limits. There needs to be more data and characteristics in the probabilistic Algorithm. The purpose of the wrapper is to eliminate redundant components that slow down the system and prevent it from performing as accurately as possible. This wrapping has the only drawback of requiring expensive calculations.

5.2 Future Work

To identify the Ancient Scripts for the Low resource languages such as Vattezhuthu, Grantha, Pallava etc., a whole framework or API may be built utilizing Deep Learning Technology. A complete framework for reading the epigraphic records may be constructed with the help of this

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preliminary model of script recognition. GAN allows historians and archaeologists to record and recover old writing.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability

The data used to support the study's findings are available from the corresponding author upon request.

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