Original Article

Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation

Chandrakala HT [1,✉], Yashas N. Gowda [2], Thippeswamy G [3]

1. *Computer Science, Government First Grade College, Gouribidnur, Chikkaballapur, IND*
2. *Computer Science, Florida State University, Tallahassee, USA*
3. *Principal, Nagarjuna College of Engineering & Technology, Bangalore, IND*

Received: April 16, 2026 | Review began: April 27, 2026 | Review ended: May 26, 2026 | Published: May 26, 2026

Abstract

Character recognition of historical handwritten stone inscription documents is a significant challenge for machine learning algorithms due to the following inherent complexities of these texts: (1) Since these documents are aged and heavily degraded, characters are superimposed with unwanted artifacts such as stains, deformations, and clutter. (2) Characters are not very legible, as they contain spurious strokes due to the extension of ascenders and descenders of adjacent overlapping characters. (3) Owing to the irregularity and variability of the script, multiple variants of the same character are present, which can lead to ambiguity in interpretation. This paper presents a use case of historical handwritten character recognition on a newly compiled EHHKSI (Estampages of Historical Handwritten Kannada Stone Inscriptions) character dataset. The following experiments were conducted on this dataset: (a) transfer learning of various convolutional neural networks (CNNs) and (b) data augmentation. The best recognition accuracy was achieved using the Xception CNN model coupled with data augmentation.

Categories: AI applications, AI/ML-based decision support systems, Image Processing and Analysis

Keywords: historical handwritten documents, stone inscriptions, character recognition, classification, xception, deep learning, data augmentation

Introduction

Kannada is one of the oldest languages in the world. It has added rich oral tradition to the world cultural heritage since the 3rd century BCE. It is the official language of Karnataka, which is a native state of India. Karnataka has an enormous amount of Kannada stone inscriptions covering a wide geographical and chronological range. These inscriptions bestow information about the early and medieval history of the state. They are the most prime and genuine resources for the study of social, political, literary, and cultural history of ancient Karnataka. The text on these inscriptions is inscribed in Halegannada, which is the older version of the Kannada language. The modern community cannot recognize this text, as the writing styles and scripts are very different from the contemporary ones. Only expert epigraphists can decode and interpret this information and publish it in modern Kannada for the benefit of historians, linguists, and researchers.

Unfortunately, these precious heritage documents are endangered due to aging, harsh environmental conditions, and risky handling. Ensuring that they do not become extinct will allow them to continue serving as references for further research. Digitization of inscriptions increases their shelf life and provides easy access and inheritance of this antique treasure. Therefore, in modern times, archaeological agencies all over the world have undertaken substantial digitization ventures to digitize their epigraphic corpus. They now preserve and maintain their digitized inscriptions in digital libraries. However, these scanned and digitized documents cannot be edited, interpreted, or queried for their contents.

In order to address this problem, an efficient character recognition technology is required to convert the historical characters into electronic text. The development of such a tool is a complex task due to variable fonts, scripts, dialects, handwriting styles, and inherent degradation of the inscriptions. Moreover, due to the specificity of the Kannada script, shape complexity of the characters, and the presence of characters with similar appearance, achieving efficient accuracy in character recognition for historical Kannada is a herculean challenge. Therefore, a full-fledged character recognition system for handling the compound characters of historical Kannada is not yet available. This article proposes a character recognition model for the EHHKSI (Estampages of Historical Handwritten Kannada Stone Inscriptions) character dataset, which is compiled by preprocessing the Estampage images as per our previous work [1]. This model transliterates the character images to equivalent modern Kannada characters. Transfer learning of Convolutional Neural Networks (CNNs) is performed for character classification. In order to equalize the quantity of samples in the dataset and improve recognition accuracy, data augmentation is employed. The results of the experiments conducted have proved the efficacy of the proposed model.

The key contributions of this work are as follows:

1) Historical handwritten character recognition of a newly compiled EHHKSI dataset is performed. EHHKSI is a multiclass dataset, which is highly skewed in terms of number of samples classwise.

2) The proposed method produced promising results on heavily degraded historical documents due to stains, spurious strokes, and deformation.

3) The proposed model classifies the complete set of Kannada compound characters as opposed to the currently available models for only selected Kannada characters.

Materials And Methods

Previous works on historical handwritten character recognition

Several research works on character recognition of historical handwritten documents have been published in the literature. Initially, conventional classification methods like decision trees, support vector machines (SVM), K-nearest neighbors (KNN), etc., were used to recognize historical characters. The main challenge with these classifiers is that feature extraction, which is a prerequisite step, is a very tedious and time-consuming task. Subsequently, CNNs, which are far more efficient and accurate classifiers, became popular. These classification models come with inbuilt feature extraction pipelines, thus not requiring explicit feature extraction. Consequently, researchers in the field of historical document processing have explored CNNs for historical character recognition. Previous works on recognition of characters from historical handwritten documents are detailed further.

Traditional Classifiers

An linear discriminant analysis classifier was trained on geometric features and contextual information for recognition of characters in handwritten historical Korean documents in a study by Kim et al. [2]. The recognition accuracy of this model was 92.98%. For 8th-century Tamil consonant recognition, Rajakumar and Subbiah Bharathi [3] employed a self-adaptive SVM trained with frequency-domain and time-domain features. The reported accuracy was 95%. For character recognition of Greek historical documents, a hierarchical classification scheme based on sub-character image mass features was employed by Vamvakas et al. [4], and an accuracy of 94% was achieved. For Telugu palm leaf characters, correlation coefficient features and decision tree classifiers were deployed by Sastry et al. [5], and an accuracy of 93% was achieved. KNN and random forest classifiers trained on Locally Linear Embedding and Generalized Discriminant Analysis manifold learning features were presented by Cheriet et al. [6] for historical Arabic documents.

Character recognition of historical archive documents based on a semi-supervised labeling technique was implemented by Richarz et al. [7]. It achieved 86.2% accuracy. SVM classification in iVector space, which attained a 92.04% recognition rate on Arabic documents, was proposed by Zha et al. [8]. Histogram of oriented shape context features and artificial neural network classifiers were tried by Amrutha Raj et al. [9] for classification of Grantha script from very old palm leaf manuscripts, and 96.5% accuracy was achieved. A neural network trained on Hough features was experimented with, and an accuracy of 94% was achieved on Tamil scripts by Suganya and Murugavalli [10]. A KNN classifier, which learned the distance and histogram profiles, was tested on palm scripts written in Telugu by Vijayalaxmi et al. [11], and an accuracy of 83.2% was achieved. Chinese calligraphy classification was performed by Pengcheng et al. [12], with 95% accuracy. They used Global Image Structure Tensor and Scale-Invariant Feature Transform feature descriptors to train a modified quadratic discriminant function classifier. For character recognition of 9th- and 12th-century epigraphs, Manigandan et al. [13] trained an SVM classifier with Scale-Invariant Feature Transform features. Histogram of oriented gradient features and a KNN classifier yielded a recognition rate of 93.1% for Telugu palm leaf characters [14].

Convolutional Neural Networks

For historical Tangut character recognition, Zhang and Han [15] developed a deep learning model, which yielded 94% accuracy. A deep CNN with the RMSprop training algorithm was employed by Roy et al. [16] for recognizing compound characters of the Bangla language at an accuracy of 90.33%. A CNN for Chinese historical character recognition with an accuracy of 95.44% was proposed by Yang et al. [17]. A CNN coupled with a data augmentation technique was used by Avadesh and Goyal [18] for character recognition from Sanskrit documents, achieving 93.32% accuracy. An ACseq2seq model was developed by Ly et al. [19] for a Japanese historical document dataset. It performed feature extraction using CNN and feature sequence decoding/encoding using bidirectional long short-term memory and long short-term memory methods. A variational auto-encoder was employed by Cao and Kamata [20] for augmentation of a historical Japanese document dataset to improve the recognition rate. The K-means clustering algorithm was employed by Ma et al. [21] to cluster 142 classes of Tibetan characters, which were trained and tested on a LeNet CNN for historical Tibetan character recognition.

The training algorithms reported in the literature for training CNN models can be broadly classified into two categories: gradient-based algorithms and evolutionary computing algorithms, as stated in a study by Gunen et al. [22]. A comparative analysis of the performance of gradient-based training algorithms (i.e., scaled conjugate gradient, gradient descent, and resilient backpropagation algorithms) for a hyperspectral image classification problem is given by Gunen et al. [23]. In a study by Alzubaidi et al. [24], a report on the utilization of alternative gradient-based algorithms for classification of various datasets is given. The weighted differential evolution algorithm was suggested by Civicioglu and Besdok [25] to be more suitable for unimodal, multimodal, hybrid, separable, inseparable, and multi/single-objective real-valued bounded and unbounded problems. According to Civicioglu and Besdok [26], compared to gradient-based optimization methods, it is relatively easier to adapt evolutionary computing algorithm-based methods to the solution of non-derivative, discontinuous, hybrid, or complex problems.

Historical Kannada Character Recognition

Among the very few published works on Kannada historical documents, Mohana and Rajithkumar [27] performed detection of era and character recognition from old Kannada stone inscriptions belonging to the Ganga and Hoysala dynasties. They used a template matching scheme made up of absolute difference coefficients for comparison. Gabor and zonal features were extracted by Soumya and Hemantha Kumar [28] to train an artificial neural network classifier for recognition of Kannada epigraphs, and a recognition accuracy of 80.2% was reported. Mean, Standard deviation and Sum of Absolute difference Algorithm was proposed by Rajithkumar et al. [29] for character recognition of Kannada stone inscription images. Character recognition of Halegannada stone inscriptions was performed by Chandrakala and Thippeswamy [30] using transfer learning and AlexNet CNN, with an accuracy of 70%. Gray-level co-occurrence matrix features were utilized by Bannigidada and Gudada [31] for classification of historical Kannada handwritten documents. SVM, KNN, and linear discriminant analysis classifiers were used for recognition, and the best accuracy reported was 96.7%. A decision tree classifier trained on local binary pattern features was tested by Thippeswamy and Chandrakala [32]

How to cite this article:
HT C, Gowda Y N, G T (May 26, 2026) Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation. Cureus J Comput Sci 3 : es44389-026-00084-0. DOI https://doi.org/10.7759/s44389-026-00084-0

for recognition of the EHHKSI character dataset at 81% accuracy. Apart from these works, computerized methods were devised by Nrupatunga and Arunkumar [33] to identify and recognize ancient Kannada inscription characters. An NGFICA enhancement method was developed by Sreedevi et al. [34] to enhance degraded inscription images. A methodology for era identification of ancient Kannada inscription images was developed by Puneeth et al. [35]. An optical recognition system was presented by Bhat and Balachandra Achar [36] for identification of different time periods of Kannada stone inscription characters. Artificial neural networks were used by Mohana et al. [37] for era identification and recognition of ancient Kannada stone-inscribed characters.

Methods

Figure 1 depicts the proposed classification model. The EHHKSI character dataset consists of unequal and inadequate samples in many character classes. In order to extend the samples in the character classes, image augmentation is performed. Three affine mathematical transformations, namely rotation, translation, and scaling, are applied to augment the dataset. After augmentation, the EHHKSI dataset is split into two sets, namely the training set and validation set in a 90:10 ratio, respectively. Transfer learning of Xception CNN is performed to customize it for classification of EHHKSI characters. Then, the transfer-learned network is trained on the training set, which thus learns all the significant features of the character images in the dataset and develops feature knowledge. The validation set is given to the model and the recognition accuracy is calculated. The trained network learns the significant features of the validation set character images and, based on its previous feature knowledge about the various classes of characters, classifies the validation set into appropriate character classes.

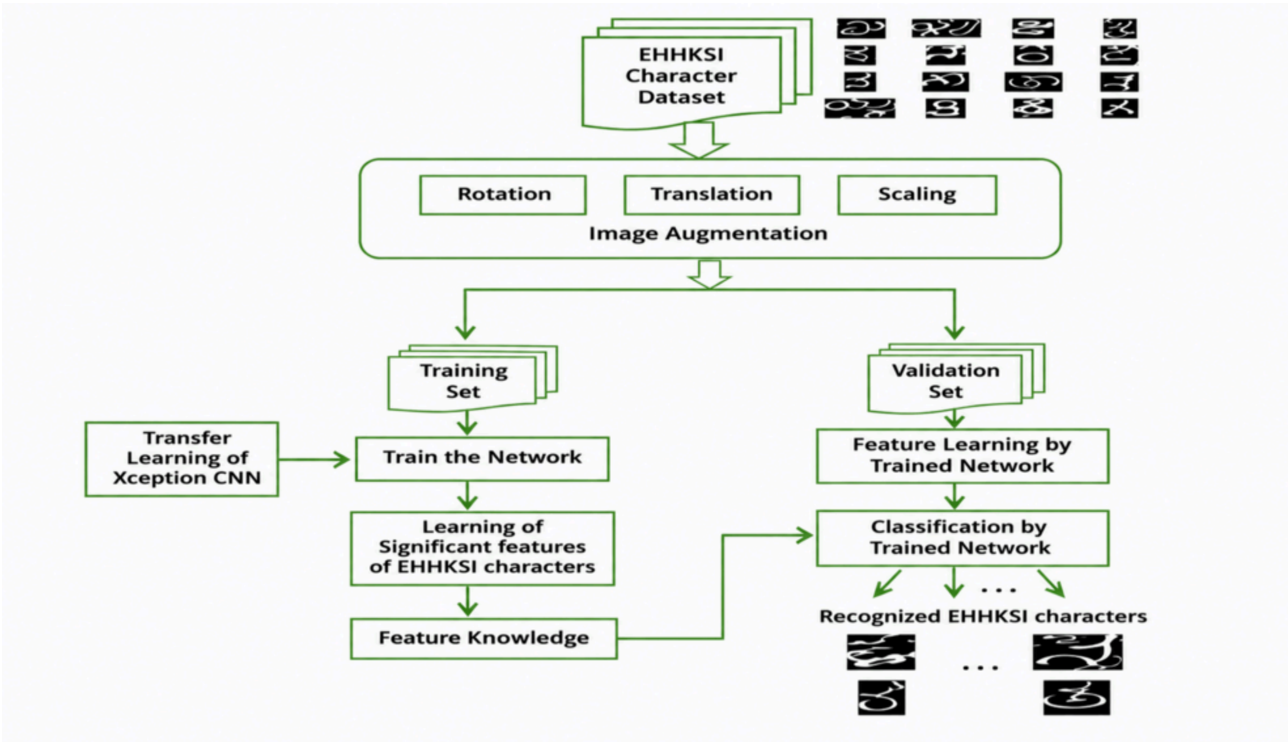

FIGURE 1: Proposed classification model

CNN, Convolutional Neural Network; EHHKSI, Estampages of Historical Handwritten Kannada Stone Inscriptions

Image Augmentation

How to cite this article:
HT C, Gowda Y N, G T (May 26, 2026) Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation. Cureus J Comput Sci 3 : es44389-026-00084-0. DOI https://doi.org/10.7759/s44389-026-00084-0

Training on a large dataset avoids the overfitting problem and gives the CNN a better chance of achieving higher validation accuracy. Augmentation of image datasets has proved to be effective in increasing the performance of deep learning models, as it can extend the size of the dataset by simulating many variations of existing images. In the proposed OCR model, image augmentation is carried out by applying three affine transformations on the EHHKSI dataset, namely rotation, translation, and scaling. Mathematically, affine transformations are performed as:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = A \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

Matrix $A_{3\times3}$ is multiplied by the vector of the original image coordinates to produce a new transformed image vector, while still preserving the characteristics of the original image [38]. For each image in the EHHKSI character dataset, rotation in the X and Y directions by ±20°, translation in the X and Y directions by ±5, and scaling by a factor of 0.0005 were performed to increase the number of samples in each character image class. Figure *2* shows sample augmentation results on one of the original character images from the EHHKSI dataset.

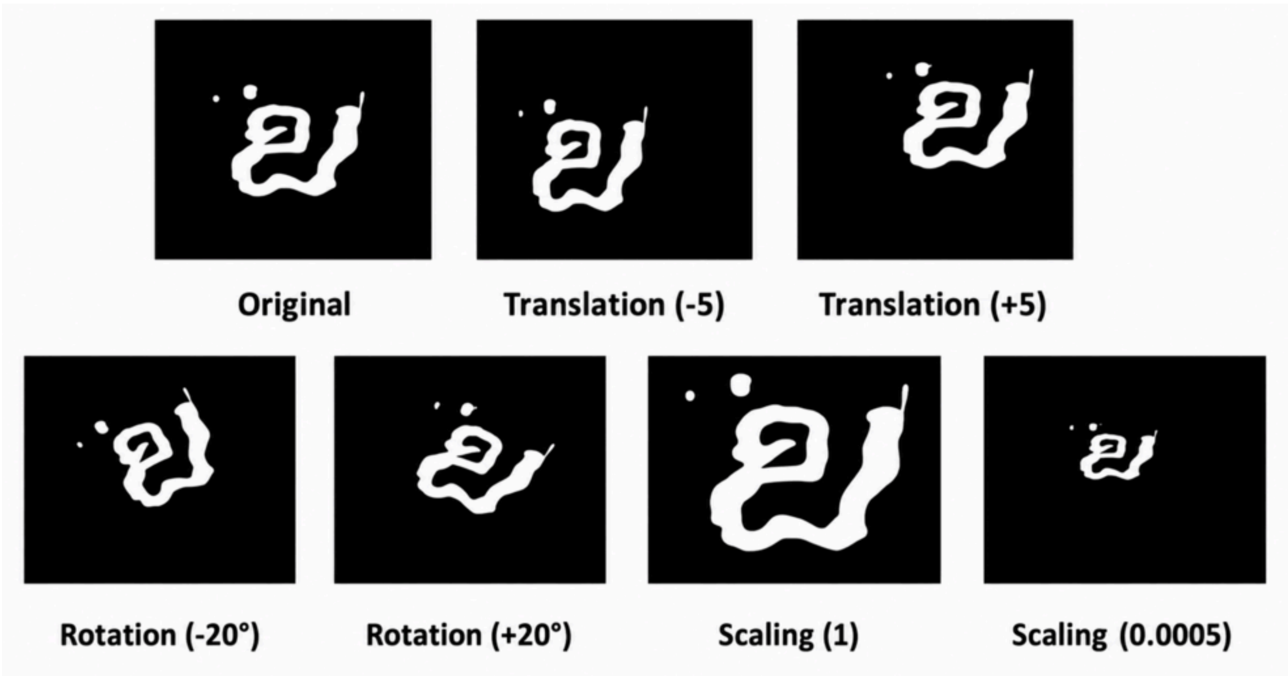

FIGURE 2: Results of augmentation on a sample EHHKSI character image

EHHKSI, Estampages of Historical Handwritten Kannada Stone Inscriptions

Transfer Learning of Xception

The pretrained Xception CNN model is fine-tuned for training on the EHHKSI dataset. The Extreme Inception (Xception) architecture improves the Inception architecture by using a linear stack of depthwise separable convolution layers with residual connections. The Xception model is divided into three parts: Entry flow, Middle flow, and Exit flow, according to Chollet [39]. The blocks of Entry flow take images of size 299 × 299 × 3 pixels and produce a feature map of 19 × 19 × 728 pixels. This feature map is further processed in the Middle flow and given to the Exit flow, which produces 2048-dimensional feature vectors that can be used for classification of the input dataset. Figure *3* shows the architecture of a single block of the Xception CNN model. Xception reduces computational complexity by increasing the width of each block and exchanging a single 3 × 3 convolution followed by a 1 × 1 convolution, while also decoupling channel and

How to cite this article:
HT C, Gowda Y N, G T (May 26, 2026) Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation. Cureus J Comput Sci 3 : es44389-026-00084-0. DOI https://doi.org/10.7759/s44389-026-00084-0

spatial correspondence. Computations are made simpler by separately convolving each channel across spatial axes. Subsequently, these axes are used as pointwise convolutions (1 × 1) for cross-channel correspondence and regularization of channel depth, as per Lo et al. [40]. Consequently, Xception can achieve higher learning efficiency and better performance without reducing the number of parameters, as per Alzubaidi et al. [24].

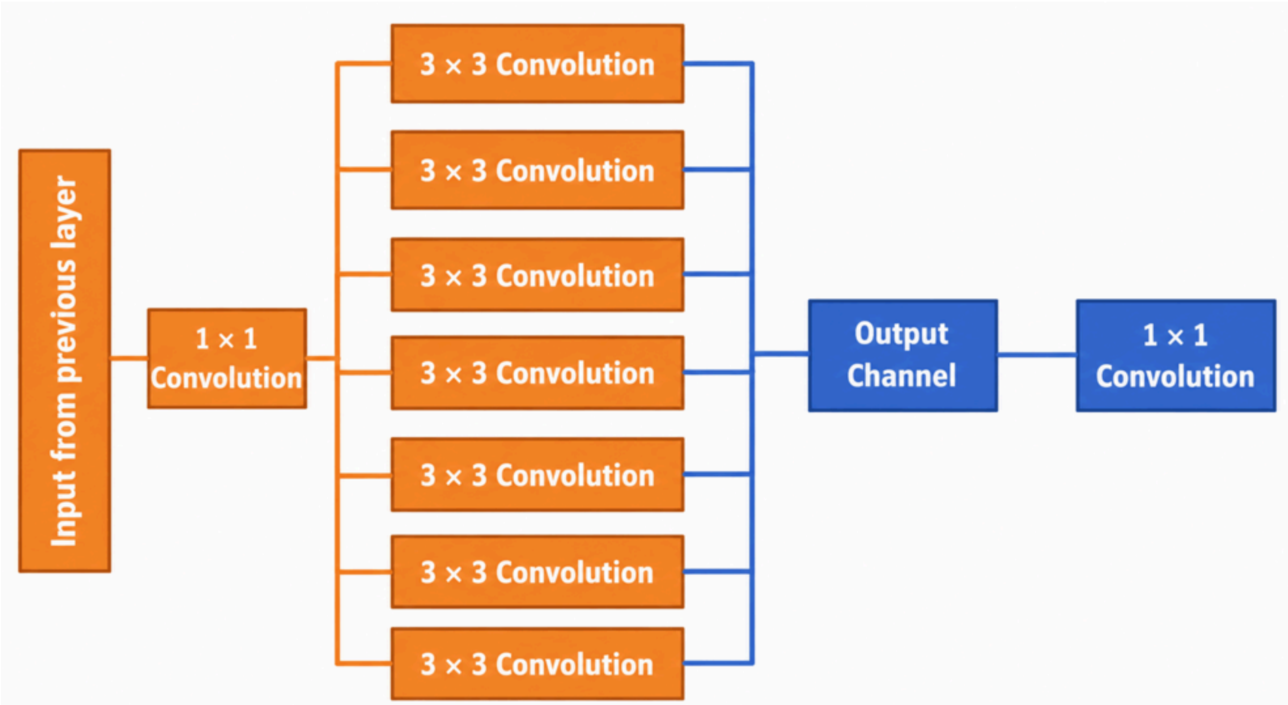

FIGURE 3: Xception block architecture

Adaptive Moment (Adam) Estimation Algorithm

Adam estimation algorithm is employed to train the Xception CNN model on the EHHKSI dataset. The Adam learning optimization algorithm is memory efficient and requires less computational power, as per Zhang [41]. It calculates an adaptive learning rate (LR) for each parameter in the model using a Hessian matrix, which employs second-order derivatives, as stated in [24], thus achieving efficient learning. It is a gradient-based algorithm that uses squared gradients to scale the LR and a moving average of gradients to improve the accuracy and training speed of the model. The Adam algorithm is based on the following mathematical equation, where ω_{ij^t} is the weight for the connection from the i-th input to the j-th neuron in the t-th layer, η stands for LR, E stands for prediction error, and ϵ is the step size:

$$\omega_{ij^t} = \omega_{ij^{t-1}} - \frac{\eta}{\sqrt{\hat{E}[\delta^2]^t + \epsilon}} \cdot \hat{E}[\delta^2]^t \tag{2}$$

The training progress plot for the Xception model on EHHKSI dataset given in Figure *4* demonstrates the learning process using Adam algorithm, and Figure *5* shows the corresponding validation accuracy plot.

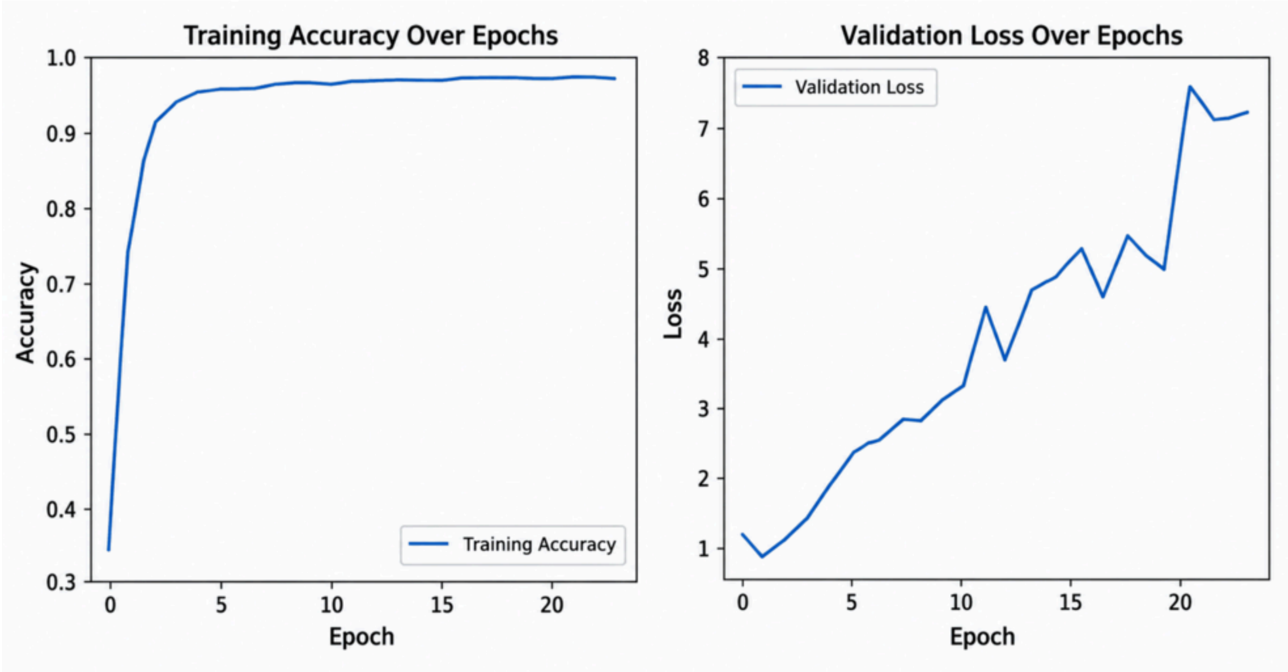

FIGURE 4: Training progress plot of Xception model

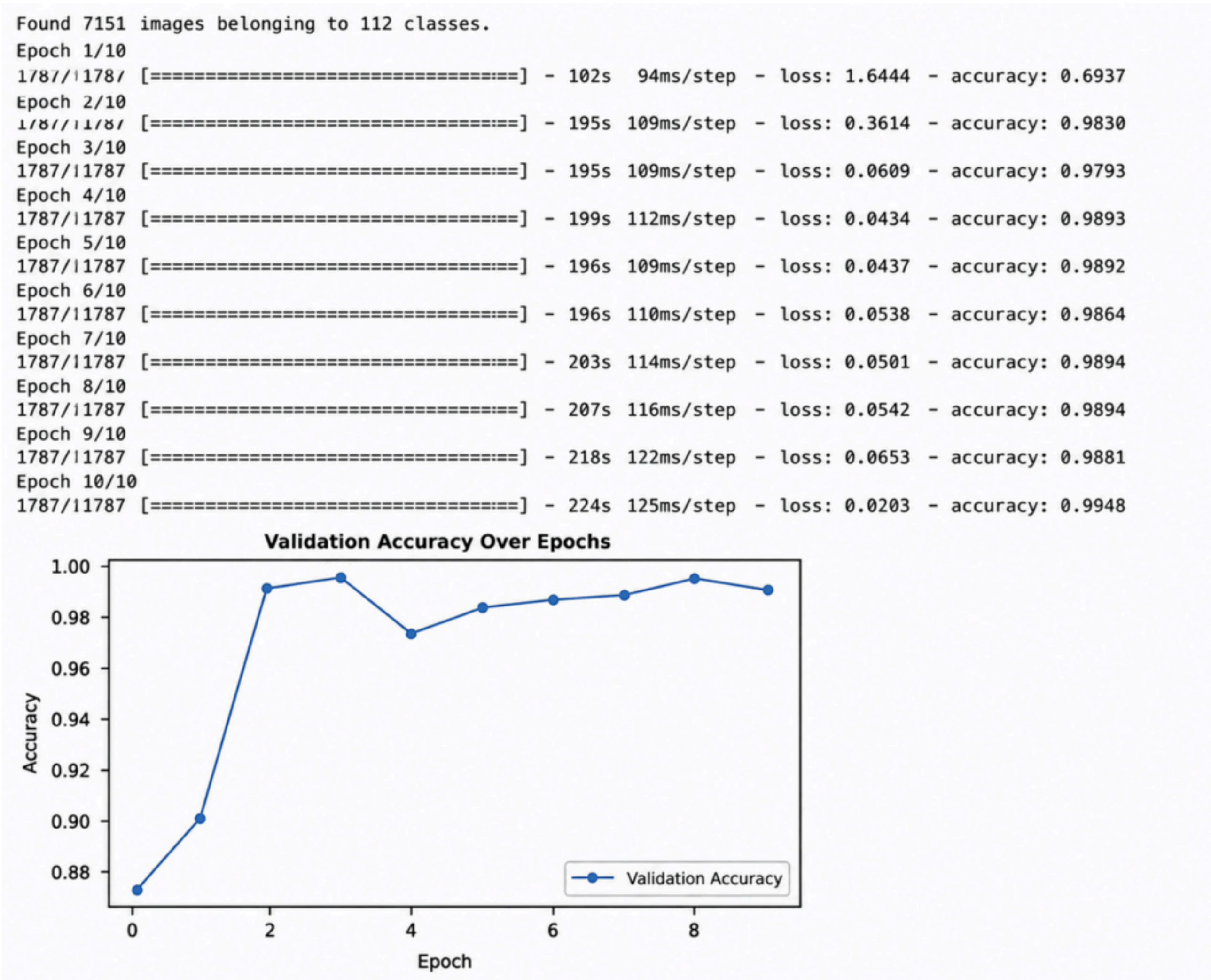

FIGURE 5: Validation accuracy plot of Xception model

Validation accuracy of the Xception CNN model is computed as the percentage of the ratio of number of labels, which are predicted correctly against the total number of labels using the below mathematical formula:

$$\text{Accuracy} = 100 \times \left(\frac{\text{number of labels predicted correctly}}{\text{total number of labels}} \right) \quad (3)$$

Results And Discussion

EHHKSI dataset

The EHHKSI data utilized for this study were obtained from the Archaeological Survey of India. This is a non-profit organization that conserves priceless historical stone inscriptions belonging to ancient times in the form of estampages. For the purpose of this study, the authors camera-captured the estampages belonging to the 11th-century Kalyani Chalukyan dynasty and prepared the EHHKSI dataset [30]. There are 14 estampage images with a resolution of 2,330 × 3,658 pixels in this dataset. These inscribed documents are written in Halegannada, an ancient counterpart of Kannada, a principal language spoken in Karnataka, a state in South India. One of the estampage images is given in Figure *6*.

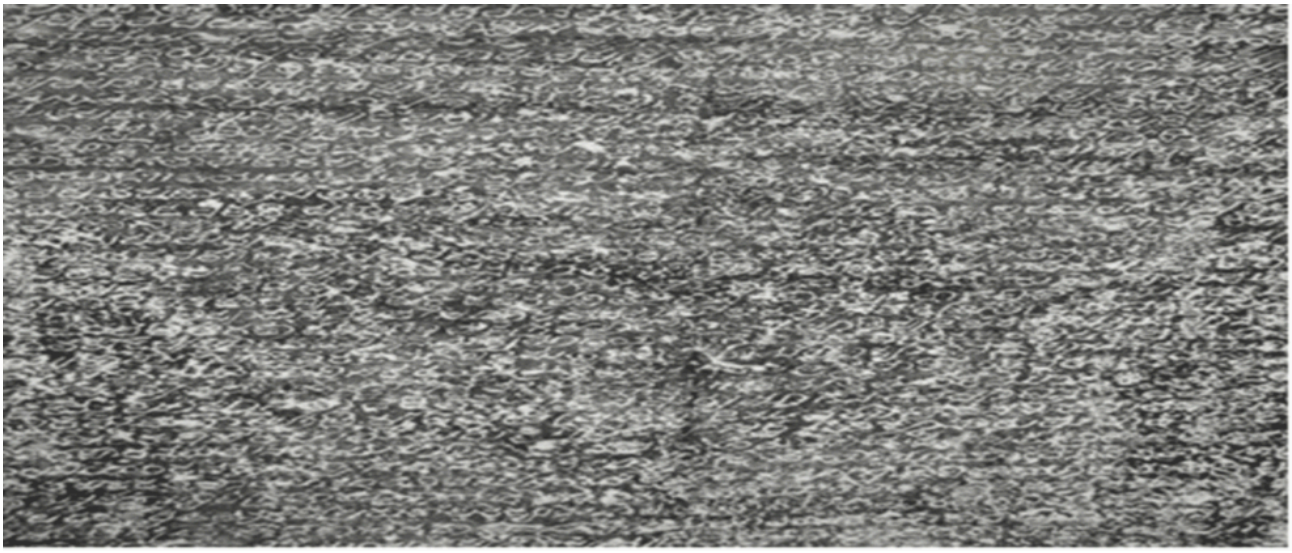

FIGURE 6: Sample EHHKSI document image

The EHHKSI images are heavily degraded. Figure 7 shows various types of degradations present in the original EHHKSI document image. As demonstrated in the figure, they are contaminated by occlusions, stains, and holes. The separation between the background and foreground text is highly unclear. Because the text is inscribed on stones, the boundaries between the text lines are muddled. Also, there are curvilinear baselines and broken and overlapping characters in these documents.

Furthermore, these credentials are handwritten. The handwritings vary among writers. Quite often, multiple variants of the same character can also be seen, due to the irregularity and evolution of the script. Not all characters are written as a single connected letter. Some characters contain spatially separated parts. This might cause ambiguity in their interpretation. Halegannada script has 13 vowels and 34 consonants. Using these base characters, a sum of 1,681 different compound characters can be formed [42]. These compound characters are of complex and nonuniform structure, and moreover quite a few of them are very similar to each other. Since all these challenges need to be tackled, it is a dreary task to build a character recognition system for this EHHKSI dataset.

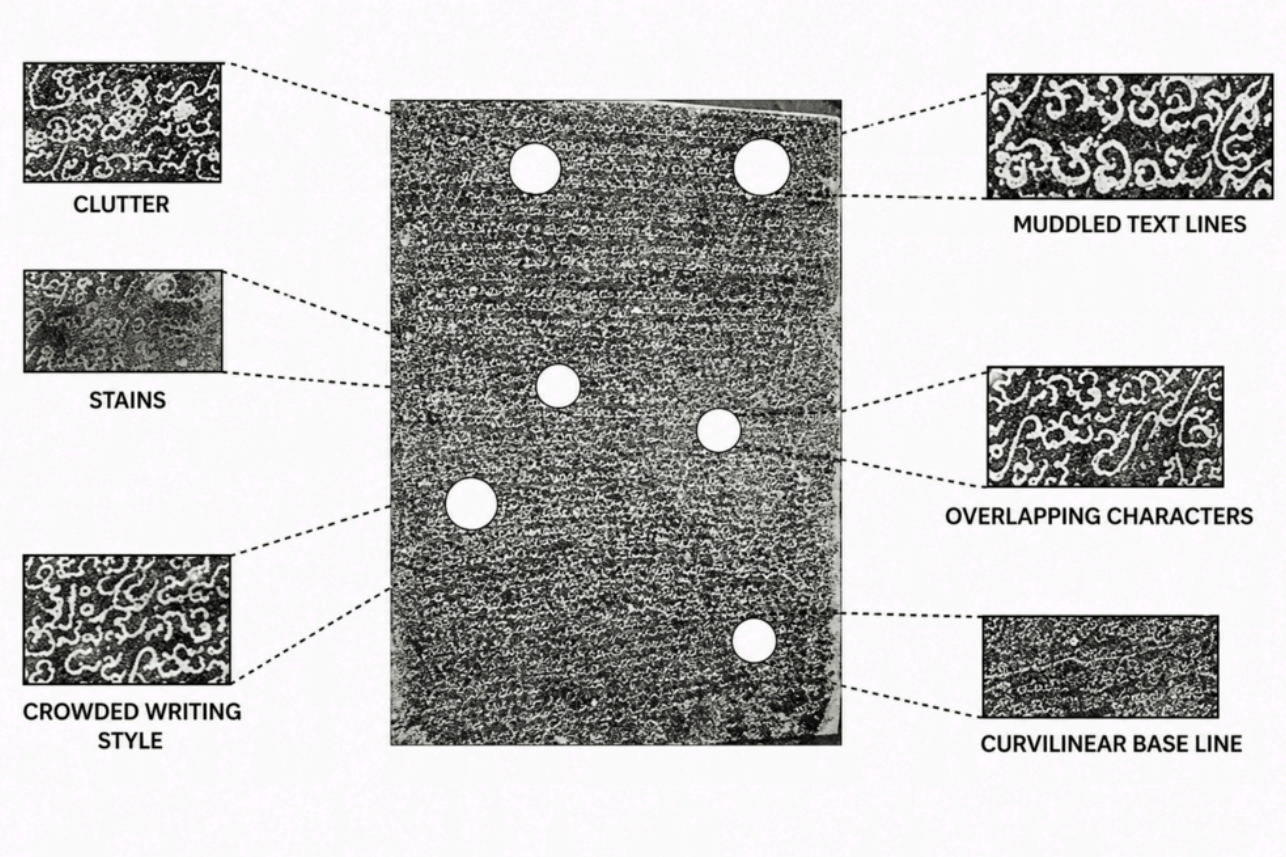

FIGURE 7: Challenges posed for the classification of EHHKSI dataset

EHHKSI, Estampages of Historical Handwritten Kannada Stone Inscriptions

Experimental setup

The EHHKSI dataset contains 1,260 character images that belong to 118 varieties of character classes. Handcrafting the most distinguishing features from such a large character set is a complex task, given that the dataset consists of many characters that are very similar to each other in terms of shape and size. Moreover, the performance of traditional classifiers is directly dependent on the efficiency of the feature extraction stage. Therefore, CNNs, which contain an inbuilt automatic feature extraction pipeline, are more suitable for the EHHKSI dataset. CNNs can learn all possible features of the given data, thus are capable of providing higher recognition accuracy. In their previous work, the authors developed a CNN classification model for recognition of EHHKSI characters [30]. However, the model suffered from an overfitting problem as the dataset is highly skewed, with a variable number of samples across various character classes. It was observed that the model could have performed better if there were an adequate number of training samples in each class of the EHHKSI dataset. In this work, the skewness problem of the EHHKSI character dataset is tackled by extending the number of samples of character images in each character class using an image augmentation technique, and higher recognition accuracy is achieved by employing an Xception CNN model.

Results analysis

An example transliteration result obtained on the validation set of the EHHKSI dataset for a few character images of the training set is shown in Figure *8a* and b.

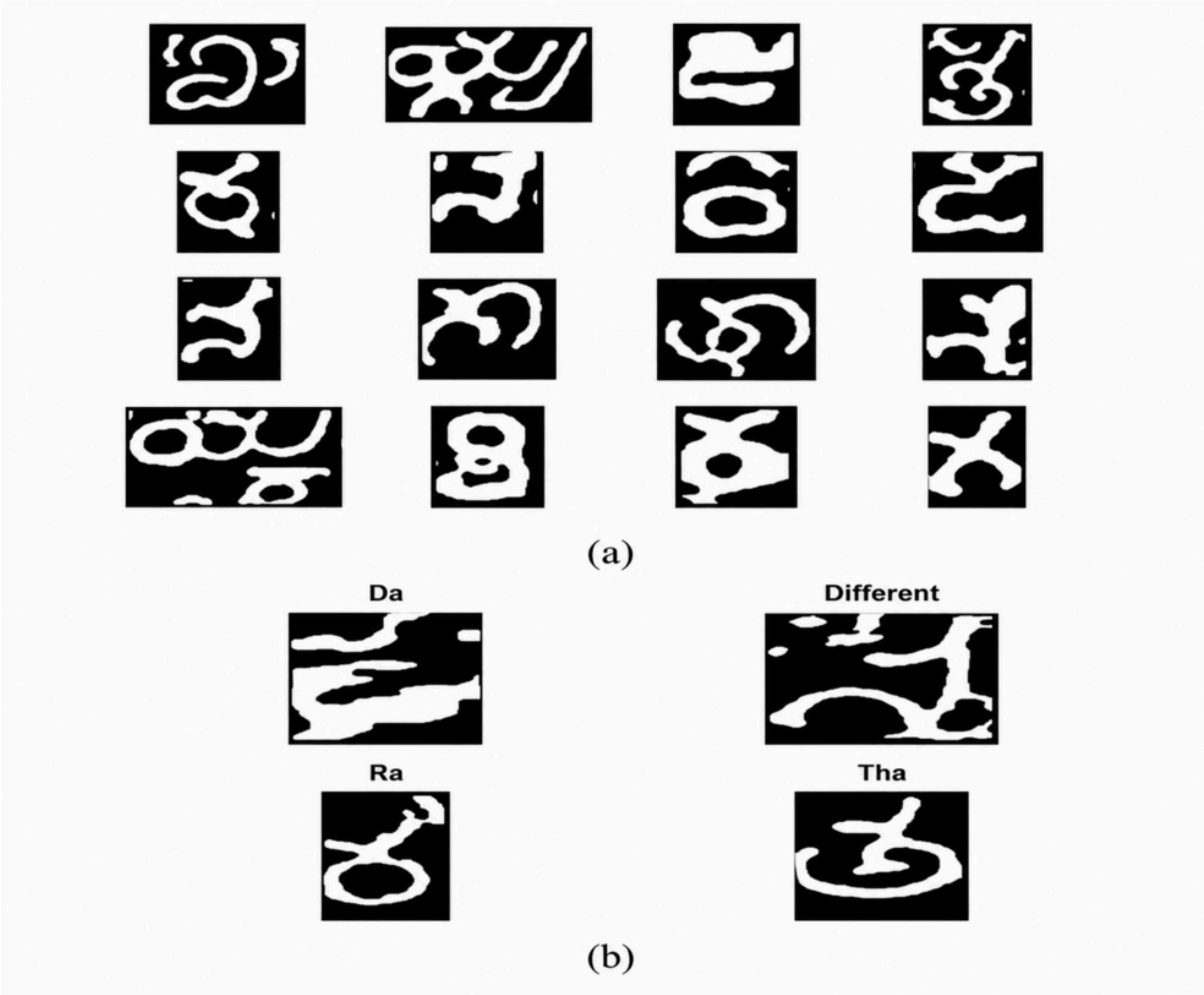

FIGURE 8: (a) Few characters in the training set. (b) Transliteration of the validation set

The precision-recall curve (Figure *9*) of the Xception classification model shows an area under the curve of 0.81, indicating that the model could achieve both high precision and high recall on the EHHKSI dataset. The multiclass receiver operating characteristic curve (Figure *10*) of the Xception classification model shows a higher area under the curve, with values in the range of 0.8 to 1.0 for all classes of the EHHKSI dataset, indicating that the model is superior and robust despite the skewness in the number of samples across the classes of the dataset.

How to cite this article:
HT C, Gowda Y N, G T (May 26, 2026) Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation. Cureus J Comput Sci 3 : es44389-026-00084-0. DOI https://doi.org/10.7759/s44389-026-00084-0

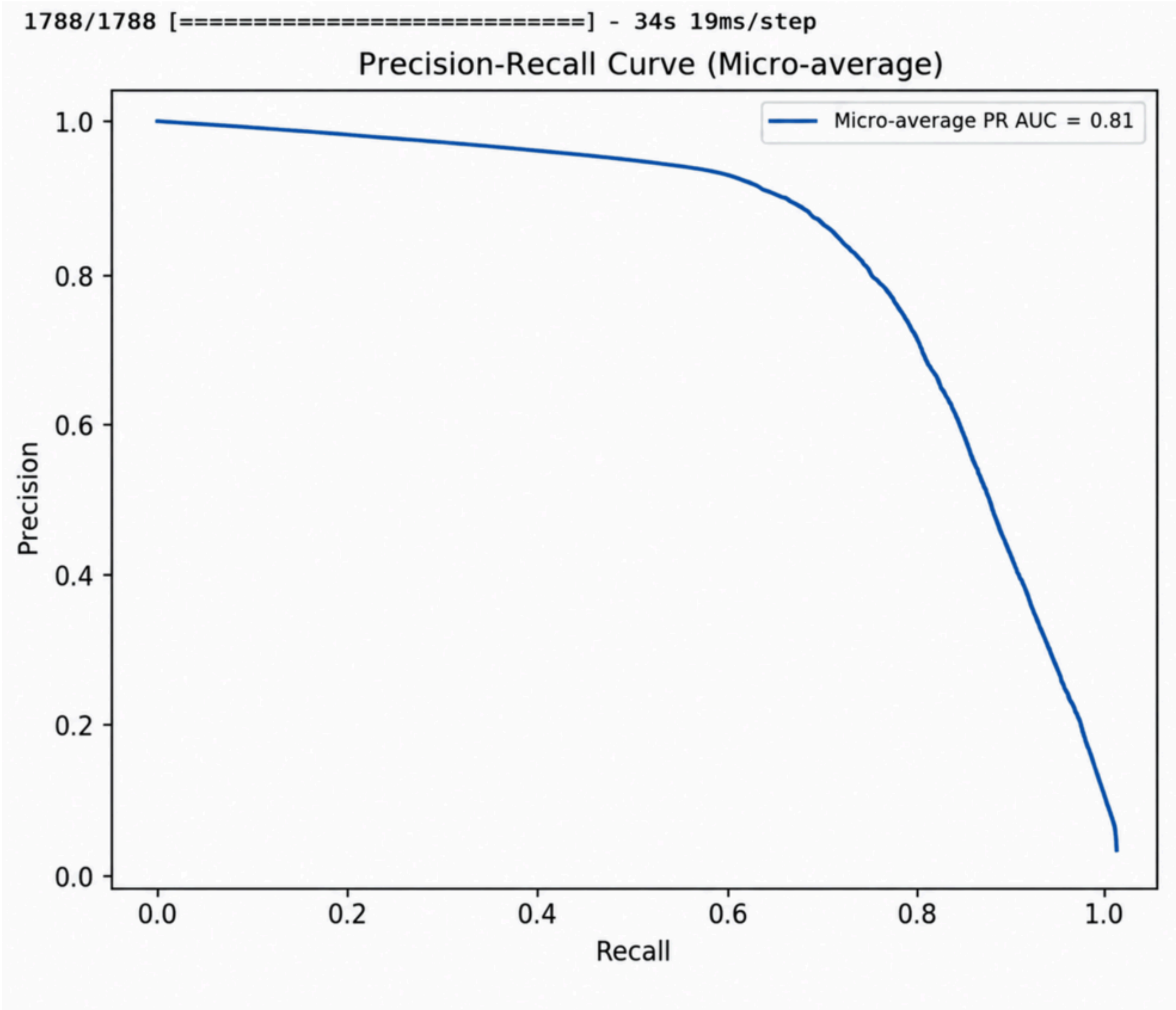

FIGURE 9: Precision-recall (PR) curve

AUC, Area Under the Curve

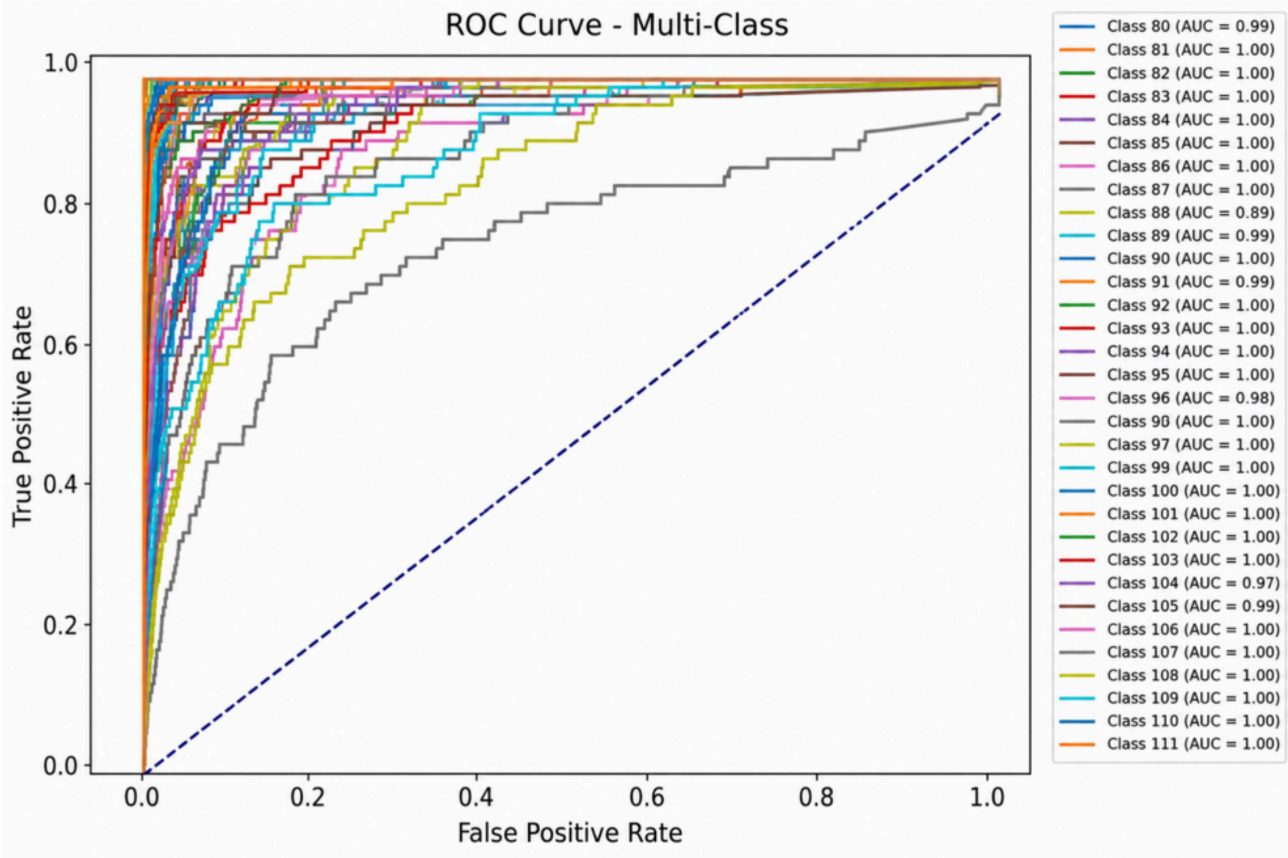

FIGURE 10: ROC curve

AUC, Area Under the Curve; ROC, Receiver Operating Characteristic

The comparative analysis of the classification accuracies achieved on the EHHKSI dataset using various classification methods is given in Table *1*.

Classification Method	Accuracy
Resnet 50	15%
Resnet 101	17%
Googlenet	22%
Alexnet CNN	45%
Decision Tree	81%
Alexnet with Augmentation	84%
Xception CNN with Augmentation	98%

TABLE 1: Comparative analysis of classification accuracies

CNN, Convolutional Neural Network

Figure 11 shows the comparison of classification accuracies graphically.

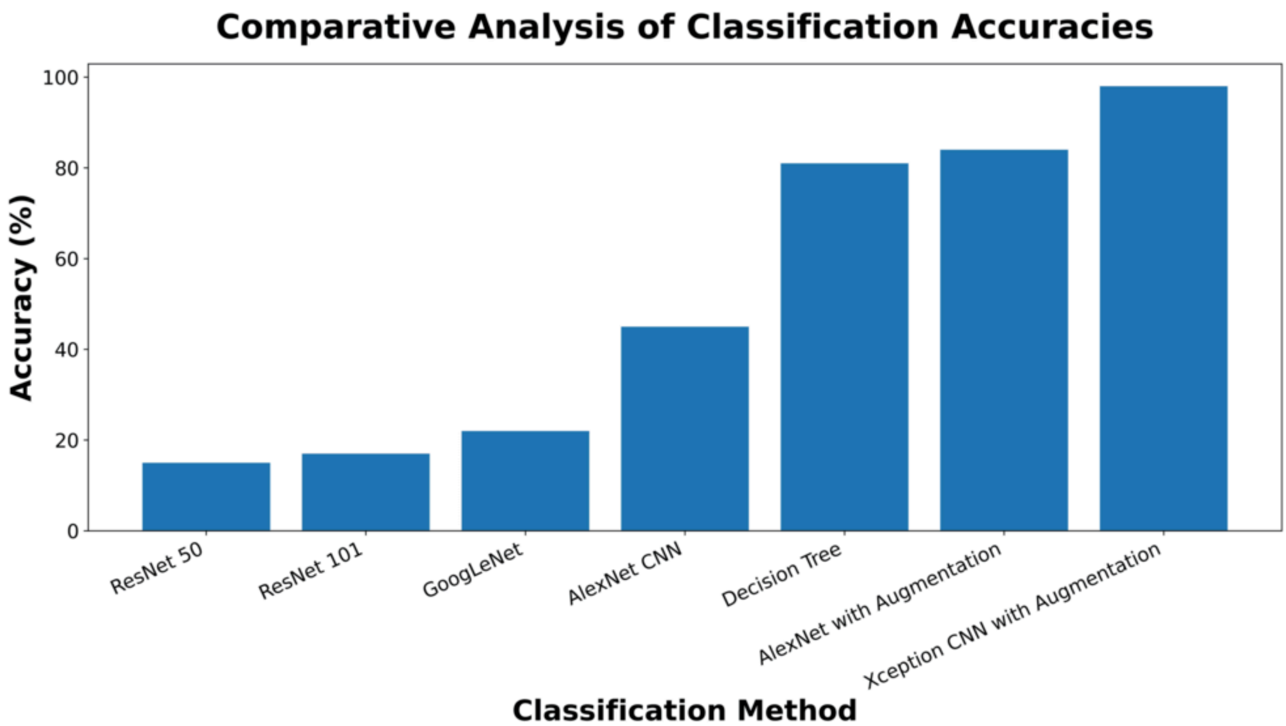

FIGURE 11: Accuracy comparison plot

CNN, Convolutional Neural Network

Conclusions

In this work, we examine a use case of historical handwritten Kannada character recognition on a newly compiled EHHKSI dataset. This dataset poses inherent challenges such as broken characters, stains, clutter, and muddled text lines. Moreover, the character set is quite large, with many characters very similar to each other. This multiclass dataset is highly skewed, as the number of training samples available is not equal. In order to perform character recognition on this challenging dataset, we introduce a transfer-learned Xception CNN model coupled with data augmentation. Various augmentation techniques have been employed to balance the skewness of the data samples, which remarkably increased the recognition accuracy of the Xception classification model to 98%.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Chandrakala HT, Yashas N. Gowda, Thippeswamy G

Acquisition, analysis, or interpretation of data: Chandrakala HT, Yashas N. Gowda

Drafting of the manuscript: Chandrakala HT, Yashas N. Gowda, Thippeswamy G

Critical review of the manuscript for important intellectual content: Chandrakala HT, Yashas N. Gowda, Thippeswamy G

Supervision: Thippeswamy G

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

Acknowledgements

The authors express gratitude to the Archaeological Survey of India (ASI), Mysore, India, for granting permission to camera-capture the estampages of 11th-century historical Halegannada stone inscriptions archived in their repository, thus facilitating the authors to conduct their experimentation on real historical data.

References

1. Chandrakala HT, Thippeswamy G, Martis RJ: Impact of total variation regularization on character segmentation from historical stone inscriptions. Pattern Recognition and Image Analysis. 2021, 31:35-48. 10.1134/s1054661821010041
2. Kim MS, Cho KT, Kwag HK, Kim JH: Segmentation of characters for digitalizing Korean historical documents. Document Analysis Systems VI. DAS 2004. Lecture Notes in Computer Science. Marinai S, Dengel AR (ed): Springer, Berlin, Heidelberg; 2004. 3163:114-124. 10.1007/978-3-540-28640-0_11

3. Rajakumar S, Subbiah Bharathi V: Eighth century tamil consonants recognition from stone inscriptions. 2012 International Conference on Recent Trends in Information Technology, Chennai, India. 2012. 40-43. 10.1109/ICRTIT.2012.6206766

4. Vamvakas G, Gatos B, Peantonis SJ: A novel feature extraction and classification methodology for the recognition of Historical documents. 2009 10th International Conference on Document Analysis and Recognition, Barcelona, Spain. 2009, 491-495. 10.1109/ICDAR.2009.223

5. Sastry PN, Krishnan R, Ram BVS: Classification and identification of Telugu handwritten characters extracted from palm leaves using decision tree approach. Journal of Applied Engineering and Science. 2010, 5:22-32.

6. Cheriet M, Moghaddam R, Arabnejad E, Zhong G: Manifold learning for the shape-based recognition of historical Arabic documents. Handbook of Statistics. Rao CR, Govindaraju V (ed): Elsevier, Amsterdam; 2013. 31:471-491. 10.1016/B978-0-444-53859-8.00019-9

7. Richarz J, Vajda S, Grzeszick R, Fink GA: Semi-supervised learning for character recognition in historical archive documents. Pattern Recognition. 2014, 47:1011-1020. 10.1016/j.patcog.2013.07.013

8. Zha S, Peng X, Cao H, Zhuang X, Natarajan P, Natarajan P: Text classification via iVector based feature representation. 2014 11th IAPR International Workshop on Document Analysis Systems, Tours, France. 2014, 151-155. 10.1109/DAS.2014.10

9. Amrutha Raj V, Jyothi RL, Anilkumar A: Script recognition from ancient palm leaves using histogram of orientation shape context. 2017 International Conference on Computing Methodologies and Communication (ICCMC), Erode, India. 2017, 790-794. 10.1109/ICCMC.2017.8282574

10. Suganya TS, Murugavalli S: Feature selection for an automated ancient Tamil script classification system using machine learning techniques. 2017 International Conference on Algorithms, Methodology, Models and Applications in Emerging Technologies (ICAMMAET), Chennai, India. 2017, 1-6. 10.1109/ICAMMAET.2017.8186731

11. Vijayalaxmi TR, Sastry PN, Rajinikanth TV: A novel 3D approach to recognize Telugu palm leaf text. Engineering Science and Technology, an International Journal. 2017, 20:143-150. 10.1016/j.jestch.2016.06.006

12. Pengcheng G, Gang G, Jiangqin W, Baogang W: Chinese calligraphic style representation for recognition. International Journal on Document Analysis and Recognition (IJDAR). 2017, 20:59-68. 10.1007/s10032-016-0277-z

13. Manigandan T, Vidhya T, Dhanalakshmi V, Nirmala B: Tamil character recognition from ancient epigraphical inscription using OCR and NLP. 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Chennai, India. 2017, 1008-1011. 10.1109/ICECDS.2017.8389589

14. Vijayalaxmi TR: Reduction of features to identify characters from degraded historical manuscripts. Alexandria Engineering Journal. 2018, 57:2393-2399. 10.1016/j.aej.2017.09.009

15. Zhang G, Han X: Deep learning based Tangut character recognition. 2017 4th International Conference on Systems and Informatics (ICSAI), Hangzhou, China. 2017, 437-441. 10.1109/ICSAI.2017.8248332

16. Roy S, Das N, Kundu M, Nasipuri M: Handwritten isolated Bangla compound character recognition: A new benchmark using a novel deep learning approach. Pattern Recognition Letters. 2017, 90:15-17. 10.1016/j.patrec.2017.03.004

17. Yang H, Jin L, Huang W, Yang Z, Lai S, Sun J: Dense and tight detection of Chinese characters in historical documents: Datasets and a recognition guided detector. IEEE Access. 2018, 6:30174-30183. 10.1109/access.2018.2840218

18. Avadesh M, Goyal N: Optical character recognition for Sanskrit using convolution neural networks. 2018 13th IAPR International Workshop on Document Analysis Systems (DAS), Vienna, Austria. 2018. 447-452. 10.1109/DAS.2018.50

19. Ly NT, Nguyen CT, Nakagawa M: An attention-based end-to-end model for multiple text lines recognition in Japanese historical documents. 2019 International Conference on Document Analysis and Recognition (ICDAR), Sydney, NSW, Australia. 2019. 629-634. 10.1109/ICDAR.2019.00106

20. Cao G, Kamata S: Data augmentation for historical documents via cascade variational auto-encoder. 2019 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), Kuala Lumpur, Malaysia. 2019. 340-345. 10.1109/ICSIPA45851.2019.8977737

21. Ma L, Long C, Duan L, Zhang X, Li Y, Zhao Q: Segmentation and recognition for historical Tibetan document images. IEEE Access. 2020, 8:52641-52651. 10.1109/access.2020.2975023

22. Gunen MA, Civicioglu P, Besdok E: Differential search algorithm based edge detection. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2016, 41:667-670. 10.5194/isprs-archives-XLI-B7-667-2016

23. Gunen MA, Atasever UH, Besdok E: Analyzing the contribution of training algorithms on deep neural networks for hyperspectral image classification. Photogrammetric Engineering & Remote Sensing. 2020, 86:581-588. 10.14358/pers.86.9.581

24. Alzubaidi L, Zhang J, Humaidi AJ, et al.: Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data. 2021, 8:53. 10.1186/s40537-021-00444-8

25. Civicioglu P, Besdok E: Bezier Search Differential Evolution Algorithm for numerical function optimization: A comparative study with CRMLSP, MVO, WA, SHADE and LSHADE. Expert Systems with Applications. 2021, 165:113875. 10.1016/j.eswa.2020.113875

26. Civicioglu P, Besdok E: Contrast stretching based pansharpening by using weighted differential evolution algorithm. Expert Systems with Applications. 2022, 208:118144. 10.1016/j.eswa.2022.118144

27. Mohana HS, Rajithkumar BK: Era identification and recognition of Ganga and Hoysala phase Kannada stone inscriptions characters using advance recognition algorithm. 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kanyakumari, India. 2014. 659-665. 10.1109/ICCICCT.2014.6993043

28. Soumya A, Hemantha Kumar G: Recognition of historical records using Gabor and zonal features. Signal & Image Processing : An International Journal (SIPIJ). 2015, 6:57-69. 10.5121/sipij.2015.6405

29. Rajithkumar BK, Mohana HS, Uday J, Bhavana MB, Anusha LS: Read and recognition of old Kannada stone inscriptions characters using novel algorithm. 2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kumaracoil, India. 2015, 284-288. 10.1109/ICCICCT.2015.7475291

30. Chandrakala HT, Thippeswamy G: Deep convolutional neural networks for recognition of historical handwritten Kannada characters. Frontiers in Intelligent Computing: Theory and Applications. Advances in Intelligent Systems and Computing. Satapathy S, Bhateja V, Nguyen B, Nguyen N, Le DN (ed): Springer, Singapore; 2020. 1014:69-77. 10.1007/978-981-13-9920-6_7

31. Bannigidada P, Gudada C: Identification and classification of historical Kannada handwritten document images using GLCM features. International Journal of Advanced Research in Computer Science. 2018, 9:1-5.

32. Thippeswamy G, Chandrakala HT: Recognition of historical handwritten Kannada characters using local binary pattern features. International Journal of Natural Computing Research. 2020, 9:1-15. 10.4018/ijncr.2020070101

33. Nrupatunga CM, Arunkumar KL: Peruse and recognition of old Kannada stone inscription characters. Recent Trends in Image Processing and Pattern Recognition. Santosh KC, Gawali B (ed): Springer, Singapore; 2021. 1380:523-529. 10.1007/978-981-16-0507-9_44

34. Sreedevi I, Pandey R, Jayanthi N, Bhola G, Chaudhury S: Enhancement of inscription images. 2013 National Conference on Communications (NCC), New Delhi, India. 2013, 1-5. 10.1109/ncc.2013.6488017

35. Puneeth P, Shashwathi Nayaka MP, Sridevi MN, Varsha S: Characterization and recognition of stone inscription. International Journal of Research in Electronics and Computer Engineering. 2019, 7:1087-1090.

36. Bhat SS, Balachandra Achar HV: Character recognition and period prediction of ancient Kannada epigraphical scripts. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering. 2016, 3:114-118.

37. Mohana HS, Rajithkumar BK, Shivakumar G, Naveen Kumar CM: Era identification and recognition of stone in-scripted Kannada characters using artificial neural networks. International Journal of Engineering Research & Technology (IJERT). 2014, 2:178-186.

38. Andersson E, Berglund R: Evaluation of data augmentation of MR images for deep learning. Master's Theses in Mathematical Sciences. LUND University Libraries, 2018.

39. Chollet F: Xception: Deep learning with depthwise separable convolutions. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA. 2017, 1800-1807. 10.1109/CVPR.2017.195

40. Lo WW, Yang X, Wang Y: An Xception convolutional neural network for malware classification with transfer learning. 2019 10th IFIP International Conference on New Technologies, Mobility and Security (NTMS), Canary Islands, Spain. 2019, 1-5. 10.1109/NTMS.2019.8763852

41. Zhang Z: Improved Adam optimizer for deep neural networks. 2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS), Banff, AB, Canada. 2018, 1-2. 10.1109/IWQoS.2018.8624183

42. Chandrakala HT, Thippeswamy G: A comprehensive survey on OCR techniques for Kannada script. International Journal of Science and Research (IJSR). 2016, 5:35-39. 10.21275/v5i4.nov162366

How to cite this article:
HT C, Gowda Y N, G T (May 26, 2026) Historical Handwritten Kannada Character Recognition Using Deep Convolutional Neural Network and Data Augmentation. Cureus J Comput Sci 3 : es44389-026-00084-0. DOI https://doi.org/10.7759/s44389-026-00084-0