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Automatic Writer Identification of Historical Kannada Handwritten Palm Leaf Manuscripts using AlexNet Deep Learning Approach

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Abstract: Ancient manuscripts have been a rich source of archeological information for decades, and some of the researchers have trying to develop Machine learning(ML) and Deep learning(DL) tools to restore the degraded information from ancient manuscripts. Today, the challenge lies in cataloging the manuscripts based on categories like subject, title, author, place, language, and script. The proposed study presents an automated deep learning model developed using the AlexNet CNN concept to classify and organize the historically significant Kannada handwritten manuscripts based on the various authors. Specifically, the AlexNet CNN approach is used to classify old Kannada handwritten manuscripts according to authorization. Old manuscripts present a unique set of challenges because they are historically significant, contain a variety of styles, and contain damaged text. The proposed research intends to present a strategy that employs deep learning techniques to attribute writing to older Kannada writings automatically. The proposed method shows promising results in several areas, i.e., the model's overall average of accuracy is 99.85%. The accurate assignment of publications to their respective authors. The classification model's performance for each class.

Keywords: Ancient Manuscripts, Kannada Palm leaf, Writer identification, handwritten documents, Deep Learning, AlexNet, Convolutional Neural Network.

1. Introduction

The proposed comprehensive research explores the feasibility of writer identification and classification for early Kannada works using state-of-the-art deep learning approaches and the AlexNet neural network. Manuscripts from different eras provide unique obstacles when studied because of their historical importance, varied writing styles, and the damage that has naturally occurred over time. Our goal is to provide a robust system that uses deep learning techniques to automatically identify the writers of historical Kannada literature, which is a rich tapestry of literature. Using HOG feature descriptors to detect and recognize the age type of historical Kannada handwritten document images proposed by Parashuram Bannigidad, and Chandrashekar Gudada. [1]. Image retrieval from manuscripts through the implementation of deep learning with a variety of fusion levels has been proposed by Khayyat., et al. [2]. DCNN are used for the categorization of ImageNet. The advancements that have been made in neural processors for information was described by Krizhevsky, A., et al. [3]. The Intelligent Coin Identification System was presented at the International Symposium on Intelligent Control in Munich, Germany, presented by Adnan Khashman, [4]. Recognition of the ancient Geez script by the use of deep learning was proposed by Demilew, F. A., and B. Sekeroglu.[5]. The application of CNN model for the classification of Indonesian historic temples described by Danukusumo, Kefin Pudi, and Martinus Maslim.[6]. Historical Currency Coin Recognition using Alexnet Model was evolved by Khandagale, H. P., et al.[7]. Machine learning algorithms for writer identification: a through evaluations. Software for working with Multimedia was explained by Rehman. et al.[8]. The classification of the degradation of an image of an ancient manuscript using DNN was developed by Saddami., et al.[9]. The technique for the classification of ancient Egyptian hieroglyphs that use deep learning was described by Barucci Andrea et al.[10]. Using LBP features to identify and categorize historically important Kannada handwritten images has been proposed by Parashuram Bannigidad, and Chandrashekar Gudada. [11]. Text classification research in Arabic language that is based on deep learning models is the subject of this comprehensive review by Wahdan Ahlam et al.[12]. The Gurumukhi script is used in the writer identification method, which is based on offline handwritten text explained Dargan, Shaveta, and Munish Kumar.[13]. The classification of Arabic text by the application of convolutional neural networks and genetic methodologies demonstrated by Alsaleh, et al.[14]. Line segmentation with GLCM for recognizing and classifying ancient Kannada handwritten scripts according to age type has been evolved by Parashuram Bannigidad, and Chandrashekar Gudada. [15].

Using deep learning techniques, many researchers have significantly contributed to other ancient languages, such as Arabic, Latin, Greece, etc. However, more research needs to be done in the Kannada language. Hence, the proposed study aims to classify Old Kannada handwritten palm leaf images using deep learning techniques. manuscripts.

2. Proposed method

The proposed research will involve many phases: data acquisition, model training, model testing, and performance evaluation. The textual collection consists of palm leaf manuscripts in Ancient Kannada script, classified as training, testing, and validation sets. The models are evaluated on the testing set following their training on the training set. This systematic approach ensures accurate classification results, and the process of selecting the most effective models for categorizing Ancient Kannada handwritten palm leaf manuscripts is simplified. Our research involved utilizing an AlexNet convolutional neural network (CNN) classifier to categorize ancient writings. 5 convolutional layers and 3 completely connected layers make up the model. Preprocessed input images of manuscripts are accepted. By employing transfer learning, we successfully optimized the model with the assistance of the handwritten Kannada palm leaf manuscripts.

2.1 AlexNet

A CNN made by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever of the Supervision group stood out at the 2010 Visual Recognition Challenge. Using GPUs and CUDA, AlexNet did 10.8% better than its closest competitor, with a 15.3% mistake rate. AlexNet was very good at putting millions of pictures into 1,000 different groups. ImageNet was used, which had 22,000 groups and 1.2 million images, making it better than CIFAR-10/100, MNIST, and CalTech-101.

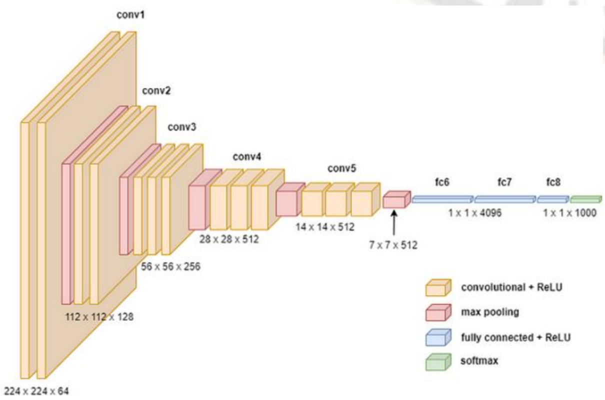

Fig. 1 AlexNet Architechure

AlexNet's architecture, as shown in Fig. 1, consists of 8 learning layers, including three fully linked layers and five convolutional layers. The last fully connected layer transforms weights into probability distributions for 100 classes using SoftMax regression. The input images are convolutional filtered using 96 11x11x3 kernels with a 4-pixel stride [2, 3]. The resolution of the input images is 224x224x3. An essential factor in the network's groundbreaking performance in picture classification is the interconnection of the third, fourth, and final convolutional layers, which do not comprise intermediate layers like pooling.

2.2 Flow Chart

The working procedure of proposed methodology includes 5 steps, which are shown in the below flow chart Fig.2.

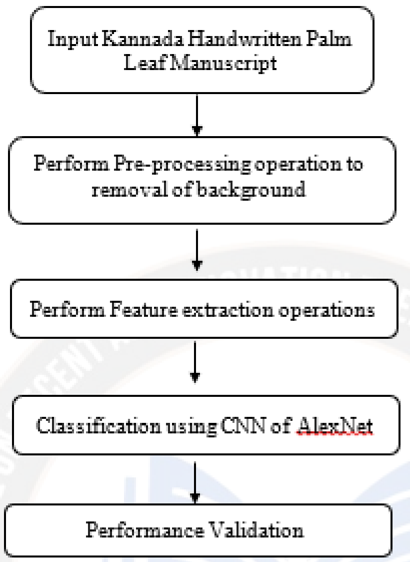

Fig. 2. Working procedure of proposed methodology

2.3 Training and Evaluation

In the present research, the dataset is divided into three categories: an 80% training set, a 10% validation set, and a 10% testing set. Each collection has eight different author manuscripts. Datasets are used to address classification problems. 1286 images are divided into 8 classes for the training set, 235 for the validation set, and 252 for the testing test.

a) Training and Testing: There are two data sets: training and testing. To train the model with stochastic gradient descent, we chose a learning rate of 0.001 and a batch size of 32. Rotation and translation methods were applied to enhance the data and improve generalizations.

A neural network model's training progress over 20 epochs is represented in this training log. The main parts are as follows:

i. Historical periods: the number of complete iterations through the whole training set. A measure of how well the model performed on the training data, loss is the value of the loss function. Performance is improved with lower settings.
ii. **Precision:** the number of training dataset values that were correctly predicted. The loss on a distinct validation dataset is denoted by val_loss. The ability of the model to generalize to new data is evaluated with its help. Less is more in this case. This variable indicates how well the model performed on unknown data by measuring its accuracy on the validation dataset.
iii. **Duration:** How long does it take for each epoch to finish?
iv. **Points of view:** Neither the loss nor the accuracy measures show any discernible upward trend as the training progresses.

The validation loss and accuracy improve at some epochs, but these benefits don't persist across all epochs. A total of 28,045,488 parameters may be trained; this model is highly complex. The depth and number of parameters suggest it was made for a relatively simple task. Actual performance, however, would depend upon several things, including the training dataset, optimization technique, and hyper parameters selected.

b) Validation: When evaluating the model, we should treat the validation set the same way as the test set. Because the order is immaterial, we can leave the "shuffle" set to true and sample each image from the validation set only once. If you plan to evaluate, set the batch size of the valid generator to 1 or a value that correctly splits the entire number of samples in the set. The assessment numbers you provided, 2.02 and 0.17, indicate a loss of around 2.03 and an accuracy of around 0.18 on the validation (test) set.

3. Experimental Results and Discussion

We acquired many ancient Kannada manuscripts, all assigned to well-known organizations by the Bangalore-based e-Sahithya Documentation Forum. The dataset contains manuscripts that span different eras, styles, and locations. Manuscript images were preprocessed to make the text easier to see and to make the image sizes consistent. The task is performed on a Windows machine equipped with a 2.30 GHz Intel i5 processor, 8 GB of RAM, and a 4 GB graphics processing unit, NVIDIA GeForce GTX 1050 Ti with CUDA, using the Anaconda3 Distribution, the Spider, and Python 3.7. The classification outcomes of medieval Kannada handwritten palm leaf manuscripts taken by the camera & represented in Figure 3a-h—sample 8 authors' Kannada handwritten palm leaf manuscript results.

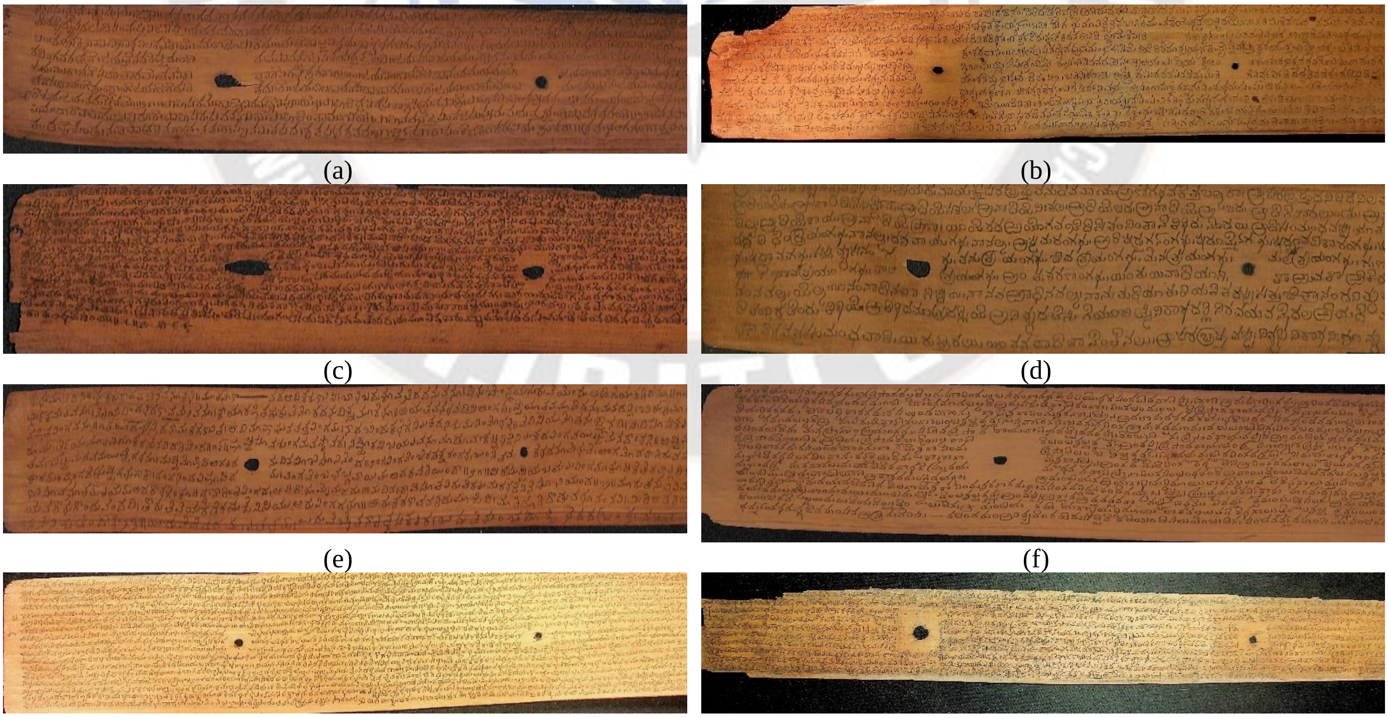

Fig. 3 a-h Sample 8 authors Kannada handwritten palm leaf manuscripts.

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After training the AlexNet with the prepared dataset, it was observed that the system's accuracy increases with higher epoch values. However, the model's superiority in convergence diminishes as the epoch value is raised to 20. The highest results in Table 1 were achieved in 20 epochs out of 1286 testing images. The outcomes obtained by the system using different epochs are displayed in Table 1.

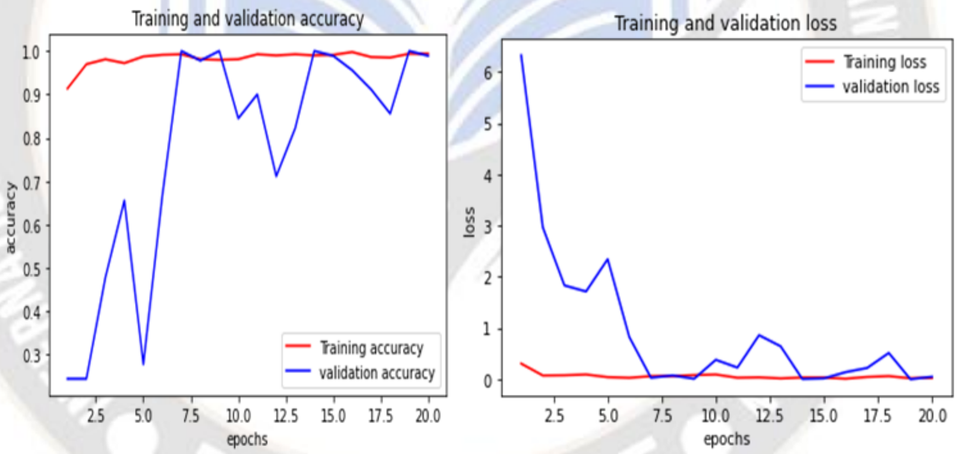
Table 1: The test results are presented in a table that is shown by the AlexNet Model.

Epoch	loss	Accuracy	val_loss	val_acc	Time
5	0.1056	0.9656	0.1552	0.9667	195s4s/step
10	0.0508	0.9911	2.7005	1.0000	186s 3s/step
15	0.0027	1.0000	2.0823	1.0000	209s 4s/step
20	0.0038	0.9987	6.2737	1.0000	197s 4s/step

The data table shows a machine learning model's training progress over epochs and performance indicators. During training, an epoch is one dataset iteration. Each epoch's loss, accuracy, validation loss, validation accuracy, and step time are in the columns. Step times were stable across epochs, with minor changes.

As a result, training a model is an iterative process that necessitates adjustments and fine-tuning to balance the model's complexity and its ability to generalize to unknown data.

All the models examined are shown in Fig. 4 a). and (b). The accuracy and loss functions are plotted against the epoch time during the training, validation, and testing. These steps are taken to learn more about the training process and to get a better idea of how reliable the networks are.



(a) (b)

Fig. 4 a). Diagrammatic representation of the proposed results of Accuracy, (b) Representation of the proposed results loss.

A confusion matrix in Fig. 5 is used to visualize the performance of a machine learning classification of the AlexNet algorithm. It is beneficial for assessing a model's performance in terms of how accurately it predicts the outcome for each class. In a confusion matrix in Fig. 5, rows reflect actual labels, and columns indicate predicted classes or labels. Each cell in the matrix reflects the number of occurrences in which the actual class matches the row and the expected class matches the column.

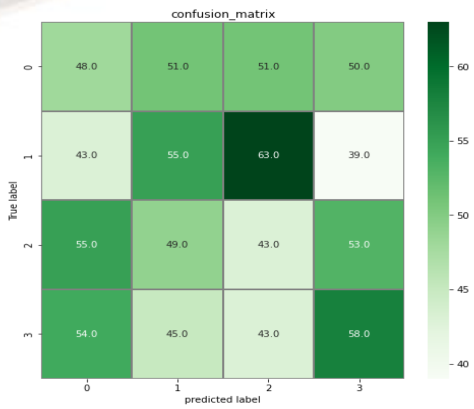


Fig. 5. Represents confusion matric by AlexNet

The classification model's performance for each class can be seen in these numbers. These numbers show how well the classification model did for each class. The AlexNet model average accuracy of 99.85% for Kannada Handwritten Palm Leaf Manuscripts.

6. Conclusion

This research presents a novel approach to writer manuscript identification of ancient Kannada handwritten manuscripts using deep learning with AlexNet architecture. The results suggest that automated classification of manuscripts by authorship is feasible and holds promise for preserving and studying these invaluable historical documents. We have shown that it is possible to automate the classification of manuscripts based on authorship with high accuracy—the classification model's performance for each class. The model's overall average accuracy of 99.85%. Future work includes expanding the dataset to encompass a broader range of Kannada manuscripts and authors. It has significant implications for preserving and studying ancient texts, making them more accessible to researchers and the wider community. Additionally, we plan to explore more advanced deep-learning architectures and techniques to improve classification accuracy and robustness further.

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