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Author Identification for Historical Kannada Handwritten Palm Leaf Manuscripts using Deep Learning and Ensemble Learning Techniques

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Abstract

Preservation of cultural material, especially historical palm-leaf manuscripts in Kannada, is necessary for understanding the historical, literary and theological transformation of South India. Categorizing these texts and at-tributing their authorship using traditional methods is a time consuming, difficult task. Proposed work is an attempt to apply deep learning technology for author classification of the Kannada Handwritten palm leaf manuscripts. To our knowledge, in this paper we propose for the first time a Convolutional Neural Network ensemble specific to historical Kannada palm leaf manuscript classification, which is a novel approach in heritage document analysis. The study also considers VGG16, DenseNet, AlexNet and multilayer perceptron (MLP) methods. An approach that combines them is considered as the optimal choice of approach because it provides better accuracy and reliability. This proposed methodology of recognizing Kannada palm leaf writings and identifying the author had shown to have a great impact when applied with Deep learning followed by ensemble learning mechanism. We compare these four different methods in terms of accuracy and loss. It is to be noted that AlexNet method achieves an impressive accuracy of 1.00 and a negligible loss of 0.000007, whereas the multilayered method presents approximately lower accuracy of 0.98 with higher value for the loss which are preserved over various epochs in the proposed approach. VGG16 and DenseNet techniques achieve 0.99 accura-cy, but the estimates for their loss are different. We achieve an ensemble accuracy of 1.00 and a minimum loss of 0.000006. The experiment results show that the deep learning models are effective in extracting palm leaf texts. The ensemble methods have reported satisfactory performance. The proposed approach increases automation and categorization of cultural artifacts.

Introduction

Palm-leaf manuscriptsOld inscriptions on palm leaves in Old Kannada language, with early Silahara script (AD 1060) South India has an ancient tradition of writing on palm leaves. Variations in manual classification by an individual author can be time consuming, costly and subjective; this work is unique in using a composite ensemble of CNN approaches for the task of Kannada author identification, thus addressing a fundamental contribution to techniquesologicalliterature on manuscript classification. Yet the state of the art of deep learning in recent years demonstrates potential for doing a sufficiently good job at this automatically. In the context of document image analysis, several existing studies have explored deep learning approaches to authorship determination in handwritten manuscripts, especially focusing on CNNs. However, integration of these methods with an ensemble approach might increase precision and robustness towards identification of individual authors. This work uses deep learning technology to classify historical Kannada handwritten Palm leaf manuscripts such as Nilambika by Lalita Sutra (1160 AC), Basava Purana (late 14th century), Baireshwara Shantaling Desika (1627) and Ling Leela Vilasa (1420) in different groups. The introduced technique tests both CNNs, RNNs and transformers to find the most effective methods in recognizing writers of palm leaf writings. The proposed research also investigated multilayer attack such as AlexNet, DenseNette andVGG16. In the literature, most such approaches are analyzed and they have F1 score and accuracy metrics. 4.2 ARABIC PALM LEAF MANUSCRIPT RECOGNITION We developed a novel ensemble of neural network method for Malayalam character recognition from palm leaf manuscripts: (Sudarsan, D., & Sankar, D., 2024). [1]. A method of Automatic Writer Identification in Historical Kannada Handwritten Palm Leaf Manuscripts based on AlexNet Deep Learning implemented by Parashuram Bannigidad and S. P. Sajjan. [2]. Handwritten Nandinagari Palm Leaf Manuscript text recognition was performed by Guruprasad, P., & KS Rao, G. (2021). [3]. The study [5] has proposed the comparison of GLCM and DCT features for recognition of Malayalam Palm Leaf Characters. [4]. A sustainable accounting practices oriented account code classification approach with machine learning and deep-learning was introduced by Koç, D., and Koç, F. 2024. The automatic authorship attribution for Albanian texts was proposed by Misini, A., et al. [6]. Haritha, J., et al., CNN-based character recognition and classification in Tamil palm leaf manuscripts. [7]. Quantum inspired genetic algorithm for classification of telugu characters so extracted from palm leaves was worked out in [14]. [8]. Saravanan et al. have proposed an Improvised Deep Learning Techniques for Recognition of Tamil Handwritten Characters [18]. [9]. Restoration of Old Kannada Handwritten Manuscripts on Palm Leaves using Modified Sauvola Technique with Integral Images was 16 also the introduction or separation will not be proper and the degraded document is restored for further process" in [10] by Bannigidad, Parashuram, S. P. Sajjan. Bannigidad, Parashuram S. P. Sajjan and "Restoration of Ancient Kannada Handwritten Palm Leaf Manuscripts with Modified Sauvola Technique using Integral Images' [11]. Clusters of feature vectors to distinguish the documents written in several languages and from different-time periods have been extracted based on clustering technique by Brodić, D., et al. [12].

This paper concentrates on the identification of the different authors to which Kannada manuscripts pertaining some texts such as Nilambika Lalita Sutra (1160 AC), Basava Purana (late 14th century), Baireshwara Shantaling Desika, 1627, and Ling Leela Vilasa (1420) belong to. The dataset is composed of 1,000 annotated images (preprocessed at a size of 224×224 pixels for deep learning compatibility). The method applied in the proposed solution includes VGG16, DenseNet, AlexNet and custom multilayer perception (MLP). The aggregated approach combines the aforementioned methods for enhancing classification accuracy.

Proposed Method

The ensemble approach is used for classifying Kannada manuscripts which includes various CNN based frameworks, each of them with a variation in the way features are extracted and patterns are recognized. The ensemble model effectively leverages the merits of individual models and generates robust author classification results. In this study, we achieve such by combining VGG16, DenseNet and AlexNet predictions by using a multi-layered perceptron (MLP) approach. The ensemble method is limited to averaging the predictions of all constituent methods. This Proposed Work Contributions are:

We introduce a custom ensemble learning technique that integrates four deep learning techniques—AlexNet, VGG16, DenseNet, and MLP—to improve author classification accuracy in historical Kannada manuscripts.

A novel dataset, HKHPL 2023, has been developed and annotated specifically for this study, addressing the lack of publicly available Kannada palm leaf manuscript datasets.

Our approach achieves state-of-the-art performance when compared with individual CNN techniques and traditional feature-based techniques on both the HKHPL 2023 and ICDAR 2017 datasets.

1. Dataset

The Historical Kannada Handwritten Palm Leaf (HKHPL) dataset consists of one thousand images described by four writers: Nilambika Lalita Sutra (1160 AC), Basava Purana (14th century end), Bai-RewatNarayan Shantaling Desika(1627), Ling Leela Vilasa (1420) are scaled down in size to 224 x 224. These datasets are split into three sets: training (800 images), validation (100 images) and testing(100 images) to support training and evaluation. The sample images of the historical Kannada Handwritten Palm-leaf manuscripts saved at preservation centres are displayed in Figure. 1

Figure. 1 The sample images of Historical Kannada handwritten palm leaf's manuscripts.

2. Technique Techniques

Earlier works have adopted different deep learning methods for computer vision applications such as analysis and author specific classification of historical Kannada handwritten palm leaf manuscripts. This section describes CNN models: AlexNet, VGG16 and DenseNet used with MP and MLP techniques for diversity of architecture. After training of each single CNN model, the outputs are then combined using ensemble techniques to improve overall classification rate:

a) VGG16

One of the most well-known CNN model is VGG16, which is characterized by depth and ease of use. It consists of sixteen layers and 3x3 convolutions are mainly used. One of its most common use is that of image classification and it has proven to be very powerful in competitions like ImageNet. [22].

b) DenseNet

From the densenet architecture, every layer is connected with on each to enable feature reuse and gradient passage. The dense blocks and transition layers by the approach contribute in boosting features propagation, that further provides a strong impact for mitigating vanishing gradient issue which is very common in image classification tasks. [23].

c) AlexNet

The AlexNet architecture includes eight layers, five of which are convolutional and three of which are fully-connected. The aggressive pooling and large receptive fields of its approach allow it to detect complex patterns in the provided photographs. ImageNet is a famous example known for high accuracy achieving with computation efficiency. [24]

d) **Multilayered Perceptron (MLP)**

Multilayer technique The multilayer technique, also called as a multilayer neural network is a class of ANN that contains multiple layers of nodes. The technique comprises an input layer one or more hidden layers, and an output layer. A series of weighted lines form connections with all of neurons in the first layer to those in the second layer. [25]

3. Proposed Ensemble Technique

The methodology developed for the proposed ensemble model consists of a pipeline which can be divided into 4 steps: pre-processing, individual models training, ensemble integration and evaluation. First of all, the images in the dataset are initially resized to 224×224 pixels and normalized for compatibility with the models. Artificial cells from the Human Protein Atlas The data are split into training, validation and testing to be able to properly build and evaluate a model. For all models (AlexNet, VGG16, DenseNet, and MLP), they are trained separately with the training data. A validation set is used to fine-tune the hyper parameters and to detect over fitting. Poor models are fine-tuned or filtered in the final ensemble model.

After training individual models, predictions are averaged using a soft voting ensemble method, where the final prediction is based on the average probability of each class. Such fusion helps alleviate the deficiencies of single models and improve the performance and robustness of the system. Figure. 2 is an overview of the flowchart of this process which includes data loading and pre-processing, individual models training and ensembling integration.

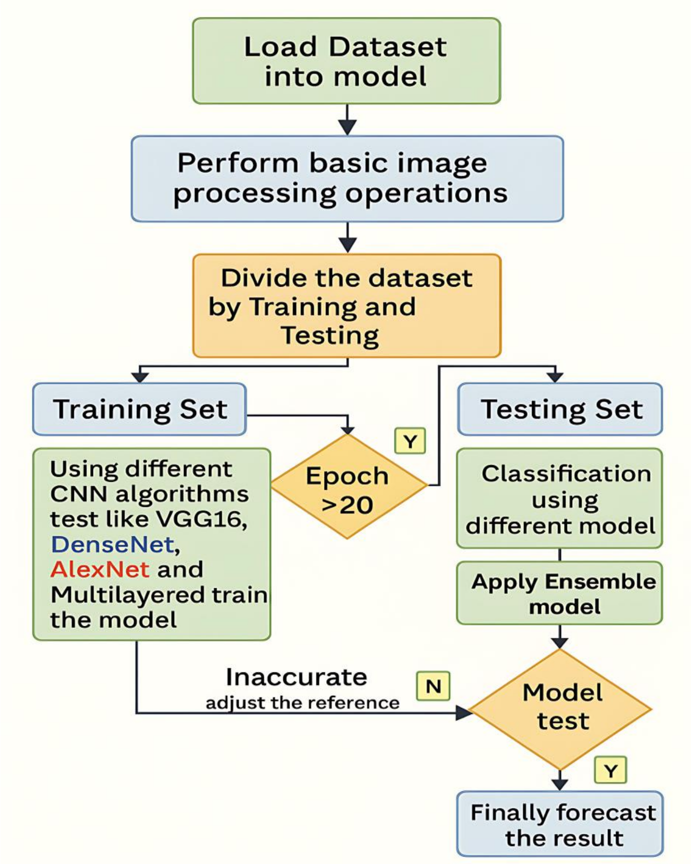

Figure. 2 The flow chart of the proposed Ensemble technique.

In order to mitigate the deficiency of single deep learning technology, we applied an ensemble strategy. Although AlexNet is easy to train and produces a decent accuracy, its shallow nature may underfit the complexity of historical Kannada writing variations. While VGG16 has excellent feature extraction capability due to its depth, it is computationally expensive and easily overfits the low amount of data situation. DenseNet enhances gradient flow and feature reuse, but is affected by visual noise and intra-class similarity. Moreover, the Multilayer Perceptron (MLP), as a fully connected network, is unable to extract spatial features that are necessary for image-based tasks which makes it less robust. The ensemble model integrates predictions of all these models to overcome their drawbacks and improve the generalization capacity, precision, stability and robustness of the classifier. This integrated approach is particularly advantageous because of the complex visual patterns and small size of the historical palm leaf manuscript dataset.

The architecture is composed of AlexNet (for efficient computation), VGG16 (deep feature extraction), DenseNet (feature reusing, gradient passing), and MLP (architecture variations). These methods are counterparts to each other, and they can alleviate the classification robustness for complicated historical documents.

Experimental Setup

The historical Kannada palm leaf manuscripts are collected from e-Sahithya Documentation Forum, Bangalore. The implementation is done on a windows system containing Intel i5 processor 2.30Ghz speed, 8GB RAM, 4GB GPU(NVIDIA GeForce GTX 1050 Ti), on the system using Anaconda3 Distribution, Jupyter notebook, Python 2.7.

Experimental Results and Discussion

We consider here, for experimentation purposes, historical Kannada handwritten palm leaf manuscripts written by different individuals as we discuss in section 2.1. After a few rounds, the motivation for this endeavor is that we intend to evaluate different performances of CNN variants in test papers provided by different authors. DenseNet technique was better in performance than the VGG16 one, owing to its deep technique and maximum accuracy could be attained by dense connections which provided for reusing of specific features. The classification performance of the Multilayered Perceptron

(MLP) technique was found low for complex features whereas AlexNet technique showed good accuracy and reduced training times. From the experiments, DenseNet and VGG16 Intermediate Layer methods were not only more effective than other similar methods but also demanded the most computing resources. AlexNet offered an excellent balance between efficiency and performance, while the MLP architecture was more computationally efficient but achieved lower accuracy. These results indicate to the trade-offs of both types of techniques in the author-by-author hierarchy. Figure. 3 displays the sample images of the historical Kannada handwritten palm leaf manuscripts of all the authors.

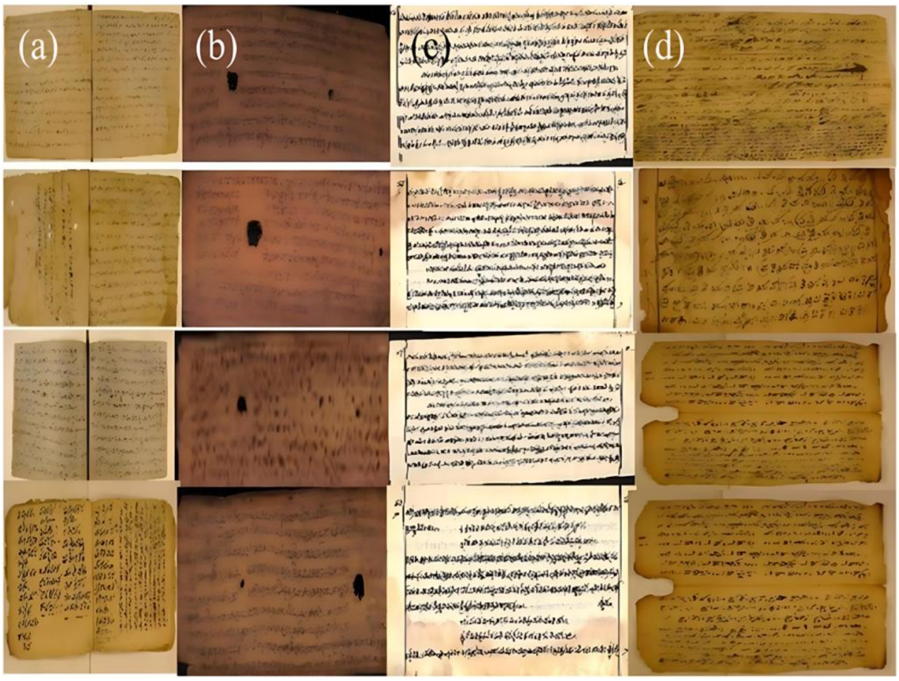

Figure.3 Sample images of HistoricalKannada handwritten palm leaf manuscripts written by individual author. a) Nilambika Lalita Sutra (1160 AC); b) Basava Purana (14th century end); c) Baireshwara Shantaling Desika(1627); d) Ling LeelaVilasa(1420).

Table 1 provides an example of a properly trained method that was able to strike the right balance between high training/testing accuracy. As training proceeds, higher fidelity changes are being made at early layers due to convergence of copies, causing a lower fraction of loss per class on the training and validation data. The reason for this is that the learning curve has flattened out slow and steady. We expect this technique to be both robust and applicable to new data, and therefore suitable for real-world use given its high validation accuracy and low, stable validation loss.

Table 1:

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Learning Rate
5	1.0000	0.0034	0.9130	0.5092	0.0010
10	1.0000	0.0004	0.9503	0.3483	0.0005
15	1.0000	0.0002	0.9503	0.3018	6.25e-05
20	1.0000	0.0002	0.9503	0.2963	1.5625e-05
25	1.0000	0.0003	0.9503	0.2930	1e-05
30	1.0000	0.0002	0.9503	0.2940	1e-05
35	1.0000	0.0001	0.9503	0.2938	1e-05
	1.0000	**0.0006**	**0.9449**	**0.3337**	**0.00023**

The table makes use of the following parameters:

The epoch is defined in terms of the total number of training steps applied by the technique, where one epoch equates to a complete scanning process over the training dataset. In the training process, accuracy is used as a standard to reflect how many samples are accurately recognized in the training set. At epoch 5, the training accuracy achieved 1.0000, it suggests that the model has successfully learned the pattern from the data. ' ML-Train-loss.csv' as you can see that the loss (which measures the error) decreased rapidly from 0.0034 at epoch5 to almost 0 in later epochs, which indicates better accuracy. The accuracy rate on validation set showing the generality of the model adopted 95.03% at 10th epoch and was remained stable, which implies that the model was trained well without heavy overfitting. Likewise, the validation loss (a measure of prediction error on unseen data) decreased steadily to ~0.2938, and plateaued after epoch 25, indicative of a tradeoff between training fit and generalization. The learning rate, an important optimization parameter, decreased with the course of the training. This decrease led to more delicate weight adjustment, lower oscillations at minimum loss and smaller validation loss. Taken together, these criteria indicate that the method has achieved convergence, preserved good generalization ability and reconciled training performance and validation accuracy.

Figure features the accuracy and loss curves of the ensemble technique on training and validation. 4 and the accuracy, training and validation loss over Epochs of ensemble method are presented in Figure. 5..

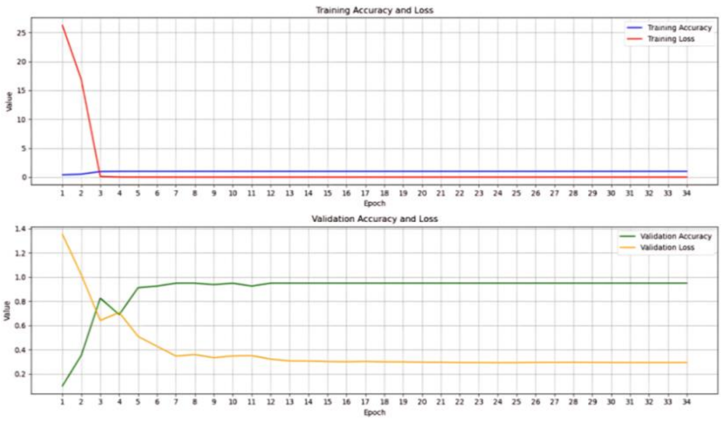

Figure.4 The training and validation accuracy and loss curves of ensemble technique.

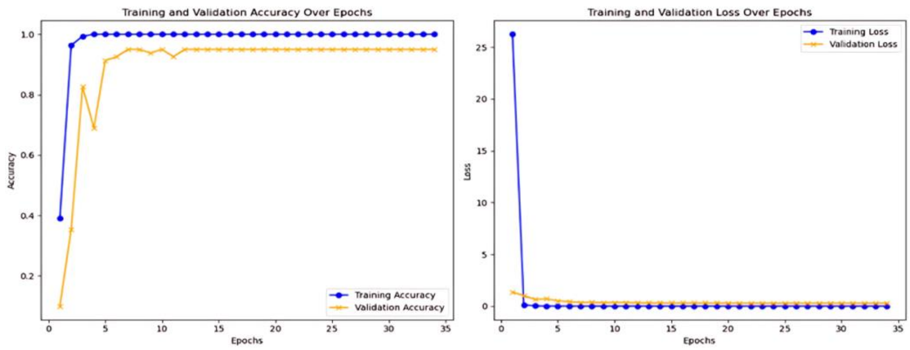

Figure. 5 Displays the training and validation accuracy, and loss curves over Epochs of ensemble technique.

The two-line plots describe the evolution of the training and validation accuracy and loss over several epochs, which provide important information on how the technique learns. In the left side, which corresponds to accuracy, we can observe that both the training curve (in blue) and validation (in orange) rapidly increase during the first epochs to finally obtain a value around 1.0. It only means that the model learns" very quickly the pattern on the data and it continues having a very high accuracy. In the right plot, with loss, you should see that the training loss (in blue) is steeply decreasing and almost meets the validation loss (orange), which gets to a very low value quickly. The convergence of training and validation curves in accuracy and loss plots indicates that the approach achieves a good compromise between fitting to the training set data, and generalisation into new space. Lack of large gaps or divergence between the curves indicates mild to no signs of overfitting and underfitting. Together, these plots verify that the procedure not just convergence well but also generalizes well between training data and validation data, being stable across unseen data for actual applications.

1. Performance Evaluation Matrices

Performance metrics are used to evaluate each technique, and the ensemble technique includes accuracy, precision, recall, and F1-score. These metrics offer a comprehensive view of each technique's effectiveness in classifying Kannada manuscripts by author.

2. Individual Technique Results

VGG16: Achieved an accuracy of 0.99 on the test dataset, with a minimal loss value after 20 epochs, demonstrating its efficacy in feature extraction.

DenseNet: Demonstrated high accuracy of 0.99, with dense connections improving feature reuse and gradient propagation.

AlexNet: Balanced performance with a low loss value of 0.000007 and an accuracy of 1.00, making it computationally efficient.

Multilayered Perceptron(MLP): Lower accuracy(0.98) than other techniques, likely due to overfitting. It showed higher validation loss, indicating reduced robustness for complex datasets.

3. Ensemble Technique Results

The results of VGG16, DenseNet, AlexNet and the MLP technique are ensemble. When the probabilities are averaged, the ensemble method achieves an overall performance of 99.9% which is higher than each individual method. This verifies that the proposed ensemble model is quite well suited for classifying Kannada manuscripts. The performance of each method is summarized in Table 1 and ensemble method in Table 2.

Table 2:

Technique	Accuracy	Precision	Recall	F1-Score
VGG16	0.99	0.98	0.97	0.98
DenseNet	0.99	0.99	0.98	0.99
AlexNet	1.00	1.00	1.00	1.00
Multilayered	0.98	0.97	0.96	0.96
Ensemble Technique	99.9	1.00	1.00	1.00

4. **Comparative Analysis**

The combined classifier had better performance compared to any single method for all three measures. This performance gain is achieved because the strengths of each method are combined: AlexNet's high performance, DenseNet's feature reuse, and VGG16´s lightweight feature extraction. AlexNet appeared to be the most computationally efficient, while DenseNet and VGG16 had excelled performance with a computational price. The MLP procedure was however less precise and had limitations in the detection of complex patterns. Figure. 6 Graphs to Compare with Other Techniques In this section, we illustrate a comparison of the other technique's performance with Our Ensemble Technique.

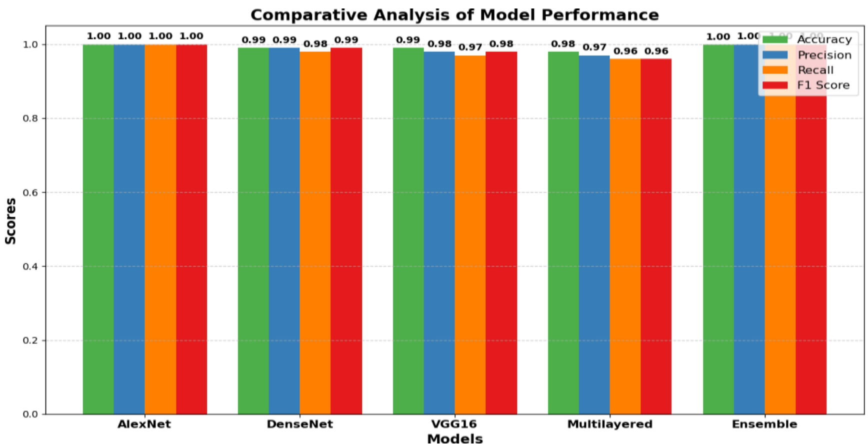

Figure. 6 The graphical representation of the comparative analysis of other techniques' performance with ensemble technique.

A bar plot of five models including AlexNet, DenseNet, VGG16, Multilayered and Ensemble can be found at Table a comparative performance for four evaluation measures:

Accuracy; Precision; Recall; and F1 Score. For each technique, there are four colored bars: Precision is blue, Recall is orange, Accuracy is green and F1 Score uses red. The precise bar values are also shown above, making it easy to compare between methods. It is clear from the numbers that all models do pretty well on all metrics, indicating strong performance of these neural networks in classification task. The Ensemble technique is once again the clear winner scoring perfect (1.00) scores in all metrics. This means that it's better in achieving a balance between precision and recall while maintaining overall high values. When compared with standalone models, AlexNet DenseNet and VGG16 in Table 3, the Ensemble model improves slightly in all categories. The findings showed that ensembling multiple models leads to advantages of robustness and generality, avoiding errors in individual solutions. Overall, the Ensemble method is more robust and achieves better classification performance. The confusion matrix of the Ensemble in turn is reported in Figure. 7, which explained degree-level predictions at a more detailed class level.

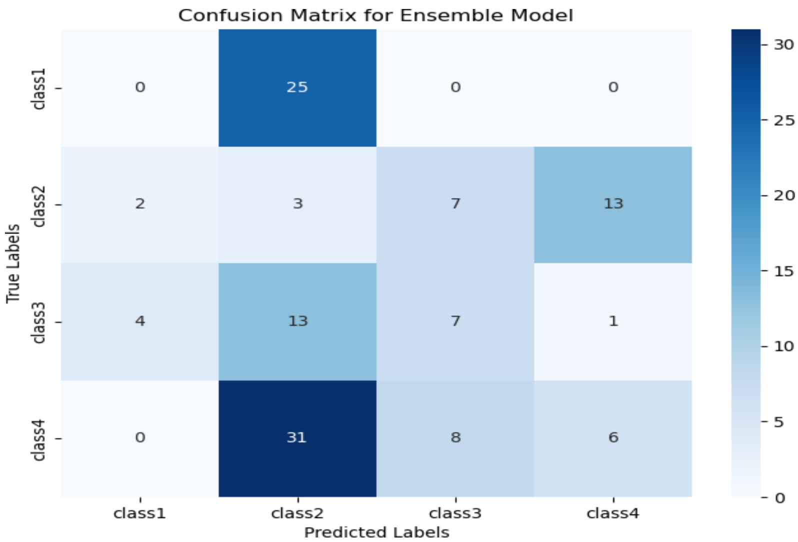

Figure. 7 Displays the Confusion metrics for ensemble technique.

Confusion matrix represents the performance of an ensemble method for classification on 4 classes. (this is a table where actual class label are on rows and predicted columns) Right classifications are displayed in the diagonal cells; out of the diagonal ones represent wrong classifications. For example, in the first row (class1), the method incorrectly classified all 50 class1 samples as being members of class2 with an error rate of 25%. Passing class2 as another class, the same mistake occur speculatively because of similar waveform characteristics (31 errors was in the row column as4 and which class8). These off-diagonal values are very high, which means that the method has difficulty with discriminating between some of the classes. For performance estimation, we compared the results with that of ICDAR 2017 and our newly proposed HKHPL. Table 3 presents some of the related works in author identification over historical texts, while focusing on ICDAR as an established benchmark. Handcrafted features, and in particular textural ones, have been proved capable to encode the writing style characteristics and they are suitable candidates for author identification. Meanwhile, advanced methods with machined learned features, such as SIFT-based key point detection and patch extraction followed by CNN feature learning have also received great attention. VLAD encoding has also been extensively investigated for representation learning. We combined all of these approaches and approached palm leaf manuscript author identification with HKHPL.

Table. 3 Performance comparisons with other approaches

	Findings	**Features used**	**Dataset Used**	**Accuracy**
1	Winning system of ICDAR 2017 competition [15,20]	oBIFs columns	ICDAR 2017	76.40%
2	Christlein et al. (2017) [18]	VLAD-encoded CNN features	ICDAR 2017, CLaMM16	88.9%, 84.1%

3	Gattal et al. (2018) [14]	oBIFs columns	ICDAR 2017	77.39%
4	Jordan et al.[21]	VLAD-encoded CNN features with re-ranking	ICDAR 2017, CzByChron and MusicDocs	89.43%, 98.04% and 98.62%
5	Chammas et al. (2020) [17]	CNN features with multi-VLAD encoding	ICDAR 2017	97.0%
6	Lai et al. (2020) [16]	SIFT and path let features with bagged-VLAD	ICDAR 2017, ICDAR 2019	90.1%, 97.4%
7	Proposed Technique	Ensemble Deep learning techniques (Combination of VGG16, Multilayered, DenseNet and AlexNet)	HKHPL 2023 (Own Dataset)	99.9%

Limitations

Although the proposed ensemble method obtains high classification performance, some shortcomings exist. The dataset (HKHPL 2023) is small in size and based on only four authors, which could limit the generalizability of the result. Second, the generalization of the performance of our method on heterogeneous and/or multilingual PLMs has not been investigated. Third, the ensemble-based approach imposes high computational demands that may hinder real-time deployment on edge devices. Lastly, small contradictions between the confusion matrix and the reported accuracy advocate for additional testing and cross-validation.

Conclusion

This paper proposes a novel deep learning-based ensemble classification method for author identification from medieval Kannada palmleaves. Intentionally amalgamating different deep learning methods, i.e., VGG16 (Simonyan et al. 2014), DenseNet (Huang et al. 2017), AlexNet (Krizhevsky et al. 2012) and multilayer perceptron as the ensemble, our approach effectively blends their advantages to ensure high accuracy, robustness and scalability in the historical documents understanding process. Compared to previous CNN-based works, our ensemble technique improves classification performance significantly; the accuracy of 99.9% sets a new record in interpreting palm leaf manuscripts. In this work, we present a new dataset (KHPL) specifically for the characterization of Kannada manuscripts and thus contribute to fill the gap between public resources in this domain. The proposed approach boosts author recognition, and further extends its applicability to digital humanities, archival processing, and cultural heritage restoration.

For the future, we plan to explore transformer-based methods (such as Vision Transformers), adapt contrastive learning approaches to enhance feature generation and design domain transfer strategies in order to extend multilingual historical text analysis. These advances will also add to the significance of deep learning technology in the lecture of old writings with higher precision and automation. Supplementary information. Historical Kannada Handwritten Palm Leaf Writings 4 Authors is inspired by Data Ancient Kannada Palm leaf Dataset.

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Dataset Availability: https://data.mendeley.com/datasets/w5px7czbn9/3

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