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U-NET: CONVOLUTIONAL NEURAL NETWORK FOR BINARIZATION OF HISTORICAL KANNADA HANDWRITTEN PALM LEAF MANUSCRIPTS

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ABSTRACT: Ancient documents are significant historical treasures that hold valuable information about past cultures and civilizations. Binarization ofhistorical Palm leaf'smanuscriptis a tedious task, as they contain debris, noise and degradednessin nature. The existing binarization algorithms may not effectively remove all types of noise present in the documents. Recently, growing interest has been shown in creating image approaches applying deep learning models as a result of their success in numerous vision applications. In this study, we propose a U-Net architecture which is part of Convolutional Neural Network (CNN) for the binarization of ancient Kannada handwritten palm leaf's manuscript. The proposed method of CNNs to learn complex image representations and handle the variability and complexity of the palm leaf. The performance estimation is measured by calculating Precision, Recall, F-Measure, MSE&PSNR and validating them with manual results obtained by language specialistsandepigraphist's. Additionally, the results are also compared with other standard methods, such as Sauvola and Niblack, on several datasets including H-DIBCO, AMADI_LONTARSET, PHIBD-2012 and our own Historical Kannada Handwritten Palm leaf (HKHPL) dataset. Binarization of historical Kannada handwritten palm leaf manuscripts is critical for determining ageand recognizing ancient Kannada characters. The proposed method demonstrates its efficacy in these applications and highlights the potential for deep learning models to improve binarization of historical documents.

KEYWORDS: Palm leaf manuscripts,U-Net, CNN, Segmentation, Deep learning, Binarization, ReLU.

1 Introduction

In the recent days, the research area for binarization and character recognition of historical documents has got much attention due to the valuable information contained in ancient documents about past civilizations and cultures. Binarization of historical Palm leaf documents is a difficult task, with old binarization algorithms having limitations in removing all kinds of noises present in such documents. Our study proposes a method for binarization of ancient Kannada handwriting palm leaf using a U-Net architecture is a part of Convolutional Neural Network (CNN), which leverages CNNs to learn image representations and handle variability and complexity. The input images are preprocessed to correct distortions or variations in illumination and contrast. The UNet architecture is designed for image segmentation tasks, and its unique architecture allows it to effectively handle complex and variable images. Fig 1 shows a sample manuscript of historical oldKannada manuscripts written on palm leaf.

Fig. 1. Historical Kannada manuscripts written on Palm leaf.

In this research paper is to plan and implement a UNet architecture based on theCNN for the purpose of historical Kannada handwritten Palm leafbinarization. Binarization is a critical step in the digitization process as it separates the foreground text from the background, making it easier to perform Optical Character Recognition (OCR) and other image processing tasks. In the present study tries to achieve the segmentation of historical degraded Kannada handwritten manuscripts written on palm leaf using the U-Net approach. In this area, A very little research work has been done,in the literature; U-net: Convolutional networks for biomedical image segmentation developed by Ronneberger, Olaf., et. al[1]. Technique for pixel-wise liver and tumor segmentation using bottleneck feature guided U-Net proposed by Li, S., Tso et. al [2]. Using global-local U-Nets, binarization of degraded document pictures is described by Huang, X., et. al [3]. DeepOtsu: Iterative deep learning for document improvement and binarization evolved by He, Sheng., et. al [4]. Rednet is a residual encoder-decoder network used for indoor RGB-d semantic segmentation proposed by Jiang, Jindong., et al. [5]. Issues, problems, approaches, and future directions in degraded historical document binarization was described by Sulaiman, Alaa., et. al [6]. GPU-based method for handwritten Devanagari document binarization proposed by Arora., et. al [7].Malayalam handwritten character recognition technique proposed using Residual Network enhanced multi-scaled features byNair, B., et. al [8]. An enhanced approach for binarizing and segmenting degraded ayurvedic medical prescriptions is a method to improve the accuracy of converting low-quality ayurvedic medical prescriptions into binary images and separating the individual elements within the image for further processing developed byNair, B. B., et. al [9]. K. P. Nihar, and C. K. Adarsh. A comparative binarization approach for degraded agreement document image from various pharmacies wasevolved by Nair, B. B., et. al[10].Deformed character recognition using convolutional neural networks was beendescribed by Rani., et. al [11]. Ancient Indian document analysis using cognitive memory network has beendeveloped by Kumar, Neethu S., et. al [12].Text and graphics segmentation of newspapers printed in Gurmukhi script: a hybrid approach is a method for separating text and graphic elements in newspapers written in the Gurmukhi script. It combines both traditional image processing techniques and machine learning algorithms to accurately segment the text and graphics in these documents was proposed by Kaur., et. al [13].Restoration of degraded Kannada handwritten paper inscriptions (Hastaprati) using image enhancement techniques is a process for improving the quality of faded or damaged Kannada handwriting on paper. It uses various image enhancement techniques such as contrast adjustment, noise reduction, and sharpening to restore the clarity and legibility of the inscriptions weredescribe by Parashuram., et. al [14].Early diagnosis of lung cancer with probability of malignancy calculation and automatic segmentation of lung CT scan images wasproposed by Manoharan, Samuel.,et. al [15]. The network will be trained on a dataset of historical Kannada handwritten palm leaf and its performance will be evaluated in terms of accuracy and robustness evolved by Chollet., F. et. al [20].Text Line Segmentation with LBP Features for Digitization and Recognition of Historical Kannada Handwritten Manuscripts wasdeveloped by Parashuram., et. al [21].Degraded Kannada handwritten paper inscriptions were restored using image enhancement techniques (Hastaprati) has been proposed by Parashuram Banni-gidad, and Chandrashekar Gudada [22].Images of degraded non-uniformly illuminated historical Kannada handwritten documents were restored has beed proposed by Parashuram Bannigidad, and Chandrashekar Gudada [23].Parashuram Bannigidad and Chandrashekar Gudada [24-29] suggested using Local binary patterns (LBP) characteristics to recognize and classify historical Kannada handwritten document images.

The objectives of this paper are to apply Deep learning (DL) binarization models like U-NET, RESNET, and AlexNet to improve the quality of handwritten and printed scripts, palm leaf, HDIBCO, PHIBD, and old text images by removing illumination, ink bleed, smear, and blurring.

2 Proposed Method

2.1 Convolutional Neural Network (CNN) based on U-Net Architecture

In this paper, we implemented aDeep learning binarizationtechnique for ancient Kannada handwriting palm leaf manuscripts using CNN with UNet architecture, UNet is a type of Deep learning architecture for image binarization tasks, which involves assigning each label to each pixel in an image. The "U" shape is formed by the combination of downsampling (max pooling) and upsampling (transposed convolution) operations in the architecture [1]. the downsampling path applies a sequence of convolution and pooling operations to decrease the spatial resolution of the input image, while increasing the number of features. The upsampling path then uses transposed convolutions and concatenation operations to restore the spatial resolution and recover the object boundaries in the output segmentation map. The two paths are interconnected by skip connections, which aid in preserving the fine features of the input images and preventing information loss during the downsampling process. The U-Net architecture is known for its ability to handle complex and large-scale datasets and its robustness to small perturbations in the input image.

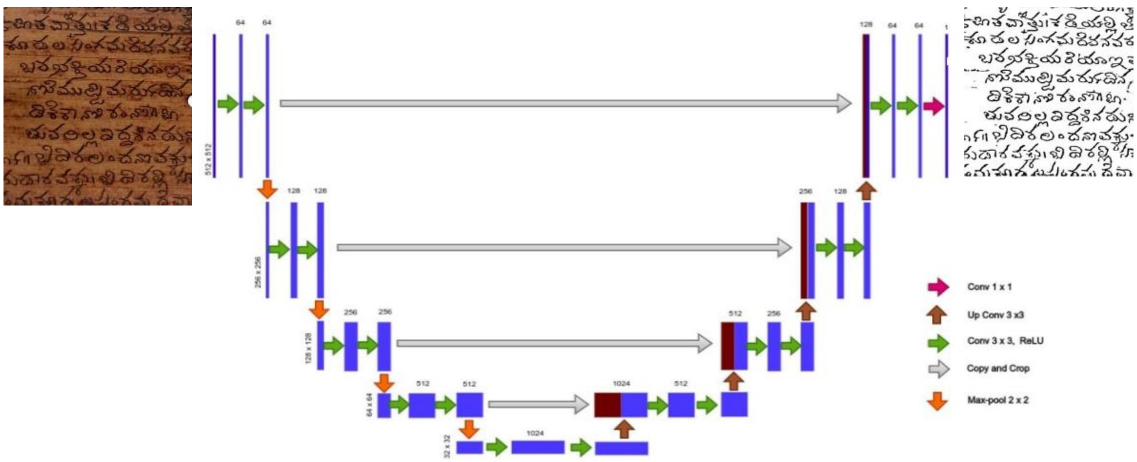


Fig. 2: Proposed modelUNetArchitecture

2.2 The algorithm of the UNet model is as follows:

The below U-Net model algorithm provides a step-by-step description of how the model works, and how it can be trained and used for image segmentation tasks.

1. **Preprocessing:** The input image is preprocessed to ensure that it is in the correct format and size, and to normalize the intensities.
2. **Convolutional layers:**Convolutional layers input the Palm leaf manuscriptsinto the first layer of the model, which is typically a convolutional layer. This layer applies filters to the input Palm leaf image and produces feature maps.
3. **The contracting (downsampling path):**The contraction path in U-Net is constructed through the repeated application of convolutions. This path is made up of four blocks: there are two 3x3 Convolution Layers, ReLU activation functions with batch normalization, and a 2x2 Max Pooling layer. The pooling layers diminish the spatial resolution and enhance the depth of the feature maps. With every pooling operation, the number of feature maps doubles while the spatial information decreases, allowing the model to become more familiar with the context of the input image. This leads to improved segmentation performance. The downsamplinginformation is then passed through an upsampling path.
4. **Bottleneck:**After several downsampling layers, the U-Net model reaches a bottleneck layer, which is a layer with a small number of filters. This layer represents a compressed representation of the input image, and is used as a bridge between the downsampling and upsampling parts of the model.
5. **The expanding (upsampling path):**The bottleneck layer in the U-Net architecture is then passed through a sequence of transferred convolutional layers. These layers improve the spatial resolution and lower the depth of the feature maps, resulting in a combination of feature and spatial information in the expanding path. This occurs through a series of up-

convolutions and concatenation operations, and the upsampling path is composed of 4 blocks, each containing a Deconvolution layer with two 3x3 Convolution Layers and a ReLU activation function with batch normalization. This makes the upsampling path nearly symmetrical to the downsampling path, resulting in the signature U-shaped structure of the U-Net architecture. The purpose of U-Net technique is to perform each pixel classification and labeling of the input image, with the final output consisting of each pixelsoftmax and cross-entropy loss function.

6. **The soft-max is expressed as in equation (1).**

$$P_k(x) = \frac{\exp(a_k(x))}{\sum_{k'=1}^{k} \exp(a_{k'}(x))} \quad (1)$$

Where,

$a_k(x)$=Feature channel k activation at the pixel location

K= No of classes (in our model k=2)

$P_k(x)$ = maximal approximation function.

Pi(x) denotes the cross-entropy at each place:

$E = \sum_{x\ \alpha\ \Omega} w(x) \log(p_{l(x)}(x))$

$$\Omega = \{0,1\} \text{true label of each pixel}$$

7. **Skip connections:** Through the skip connections, the upsampled feature maps are concatenated with the feature maps from the matching downsampling layer. This permits information to pass from the downsampling layers to the upsampling layers, which aids in the preservation of fine-grained details in the segmentation map.
8. **Output layer:** Finally, the U-Net model outputs a segmentation map, which is a label map indicating the class of every pixel in the input image. The output layer is typically a convolutional layer followed by a softmax activation function, which provides a probability distribution over the classes for each pixel.
9. **Training:** The U-Net archetypal is trained using a supervised learning method, the model is provided with characterized images and learns to predict the correct labels for new images. The training method involves adjusting the parameters of the model to minimize a loss function, which measures the difference between the predicted labels and the true labels.

2.3 The flow chart of the proposed U-Net model is illustrated in the Fig. 3.

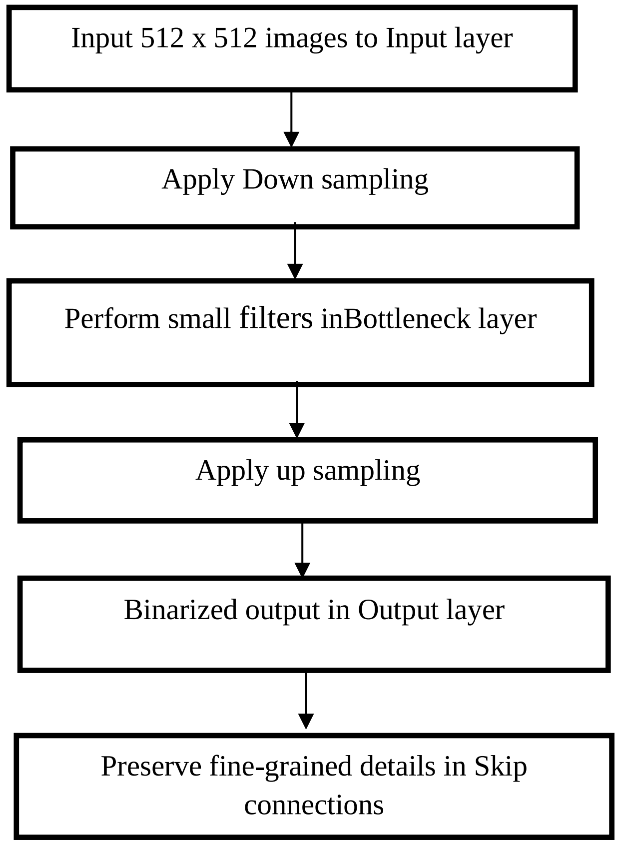


Fig. 3: Theflow chart of the proposed U-Net model.

The above flow diagram of the U-Net model is a visual representation of the proposed model architecture, and provides a sophisticated overview of how the proposed technique works. It can be used to understand the structure and behavior of the model, and to identify potential areas for improvement or optimization in Palm leaf manuscripts.

3 Experimental Results and Discussion

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, Spider, Python 2.7. Camera captures mediaeval Kannada handwritten palm leaf manuscripts are shown in Fig. 4.

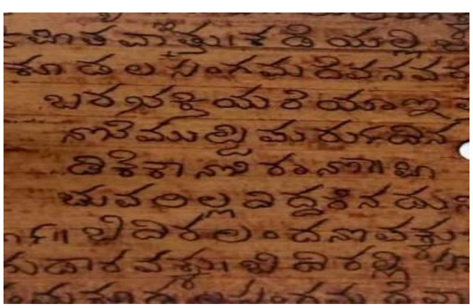
Fig.4(a) shows a typical noisy document with non-uniformly distributed noise. The image's background is golden brown in color. Original camera captured 512 × 512 RGB image shown in Fig.4(b), Ground truth of original image 512 × 512 manuscript shown in Fig 4(c), Computed histogram of the original noisy document is shown in Fig.4 (d). The anticipated result was then compared to the Souvola and Niblack which are shown in Fig.4(e)and (f). All the methods produce some noise in the manuscript while maintaining image clarity, the resulting U-Net model produced clear image as same as ground truth image are shown in Fig.4 (g).

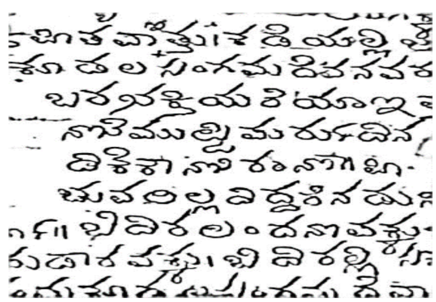
Next, the comparison of results obtained using the U-Net model and classical binarization algorithms such as Sauvola and Niblack, there results can provide valuable insights into the effectiveness of deep learning methods for historical document binarization. By demonstrating the advantage of the U-Net model in terms of accuracy and performance, it will strengthen the case for the use of deep learning model for recognition of handwritten historical Kannada manuscripts.The preprocessing steps taken to correct for distortions and variations in illumination and contrast will have a significant impact on the final results. Therefore, it is crucial to carefully evaluate and optimize these preprocessing steps before conducting the experiments.

Furthermore, conventional performance metrics such as Precision, Recall, F-Measure, MSE, and PSNR are used to evaluate the models.These metrics will provide a quantitative measure of the performance of the models and allow for a fair comparison between the results obtained using the U-Net model and the classical algorithms.

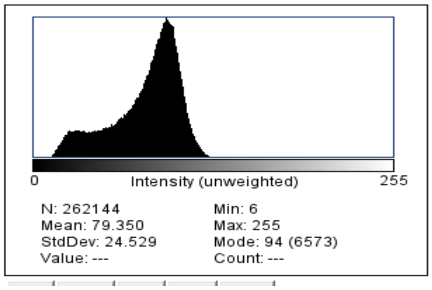
Overall, the comparison of results calculated using the U-Net model and classical binarization algorithms will provide a deeper understanding of the strengths and limitations of these methods and contribute to the advancement of the field of historical document binarization and preservation.

(a)

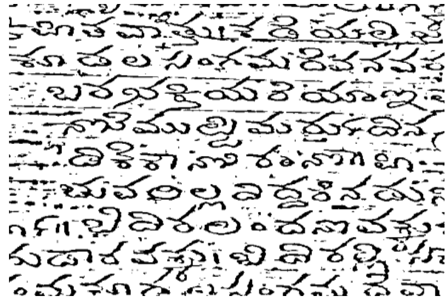




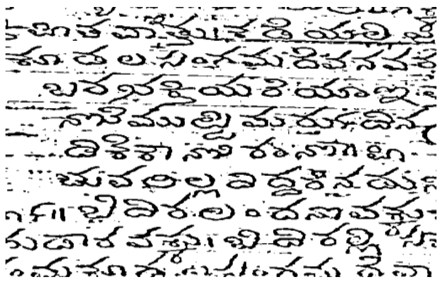
(b) (c)



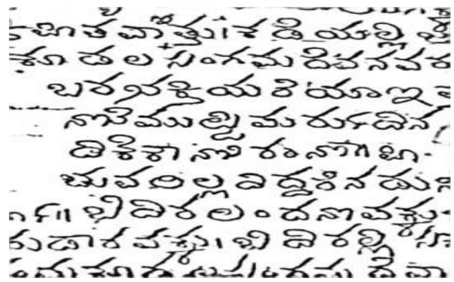
(d)



(e)



(f)



(g)

Fig. 4. (a) Sample old Kannada palm leaf image,(b) Original camera captured 512 × 512 RGB image, (c) Ground truth 512 × 512 image, (d) Histogram of the original image, (e) Savoula threshold applied original images, (f) Niblack threshold applied original images, (g) Proposed U-Netthreshold applied for original image an(b).

In the literature, several performance evaluation metrics have been employed. Out of these, five methods have shown to produce the best results when evaluating the proposed method for extracting degraded historical Kannada handwritten palm leaf manuscripts and described as below:

(i) **Precision:**Precision measures the percentage of properly binarized pixels compared to the total number of binarized pixels, which is given in equation (2)

$$\text{Precision} = \frac{tp}{tp+fp} \quad (2)$$

(ii) **Recall:**Recall measures the percentage of accurately binarized pixels compared to the total number of foreground pixels which is given in equation (3)

$$\text{Recall} = \frac{tp}{tp+fn} \quad (3)$$

(iii) F-Measure: The weighted harmonic mean of precision and recall is known as F-Measure, which is given in equation (4)

$$F = \frac{1}{\alpha\frac{1}{p}+(1-\alpha)\frac{1}{R}} \quad (4)$$

(iv) MSE:MSE measures the average difference among the binarized image and the ground truth image which is given in equation (5)

$$MSE = \frac{1}{MN}\sum\sum\left(g(x,y)\right) - (f(x,y))^2 \quad (5)$$

Where g(x,y) represents the output image and f(x,y) represents the input image

(v) PSNR:PSNR measures the ratio between the maximum power of a signal and the power of corrupting noise which is given in equation (6)

$$PSNR = 10\log\left(\frac{MAXi*MAXi}{MSE}\right) dB \quad (6)$$

The maximum image intensity is 255 when the pixel is represented in 8 bits.

The precision, recall, F-Measure, MSE, and PSNR metrics have been intended for each of the images and the results are given in Table 1. The performance of proposed method is evaluated by language experts and epigraphists. The average values of precision, recall, F-Measure, MSE, and PSNR are 0.838, 0.0124, 40.2, 0.108, and 5.442 respectively. Inthe literature, suggests that a higher precision, F-Measure, PSNR and lower recall, MSE indicate a higher quality of the image.

The assessment of the proposed techniqueis done with other standard approaches, such as Souvola and Niblack, showed that the Kannada handwritten Palm leaf characters generated by the proposed model closely resemble the original characters. A visual comparison of the results provides a clear understanding of the proposed method's performance compared to other methods in the literature.

Fig. 5.(a) Original image from the literature [19], (b) Original image from own dataset, (c) Binarized using Souvola method, (d) Binarized with Niblack method, and (e) Proposed Binarized U-Net model result.

Table 1. The results of performance evaluation of proposed method, Souvola and Niblack methods.

Binarization methods	**Performance evaluationapproaches**	**Sample images of historical Kannada handwritten palm leaf manuscripts**					
		Image 1	**Image 2**	**Image 3**	**Image 4**	**Image 5**	**Avg**
Souvola method	PSNR	5.58	5.03	4.82	4.77	4.13	4.866
	MSE	0.11	0.15	0.12	0.12	0.12	0.124
	Precision	0.012	0.013	0.013	0.015	0.015	0.0136
	Recall	0.012	0.013	0.014	0.016	0.016	0.0142
	F-Measure (%)	12	13	13	15	15	13.6
Niblack method	PSNR	6.65	4.99	4.74	4.68	4.17	5.046
	MSE	0.13	0.18	0.15	0.15	0.20	0.162
	Precision	0.012	0.013	0.013	0.015	0.015	0.0136
	Recall	0.013	0.013	0.014	0.016	0.016	0.0144
	F-Measure (%)	12	13	13	15	15	13.6
Proposed method	PSNR	7.23	5.22	4.99	4.85	4.92	5.442
	MSE	0.10	0.11	0.12	0.10	0.11	0.108
	Precision	0.83	0.85	0.86	0.79	0.86	0.838
	Recall	0.012	0.011	0.012	0.013	0.014	0.0124
	F-Measure (%)	**35**	**39**	**42**	**43**	**42**	**40.2**

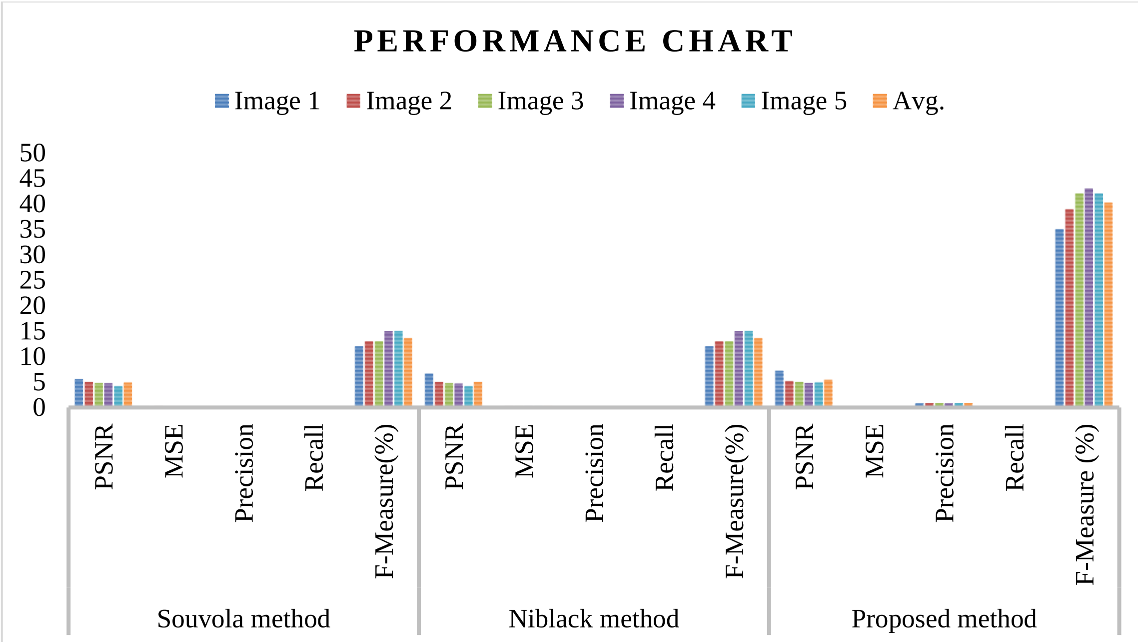
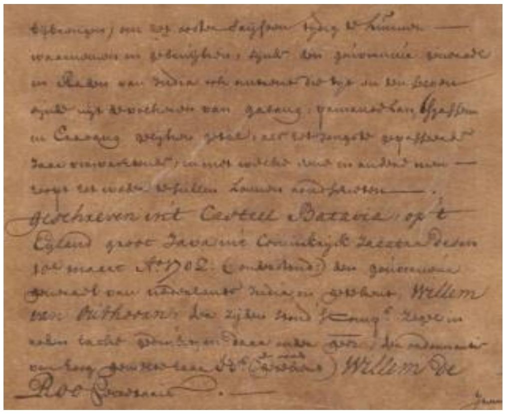


Fig. 6. Graphical representation of the proposed results with other standard methods.

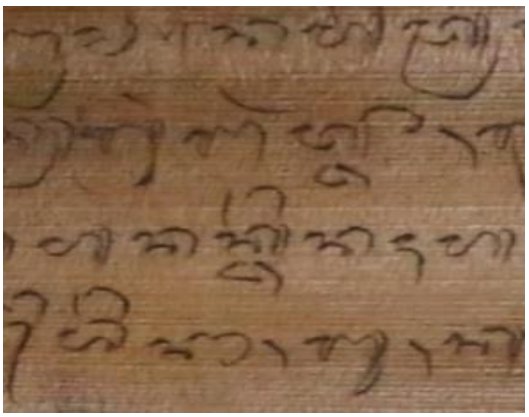
3.1 Proposed Model Comparing with different Benchmark Datasets

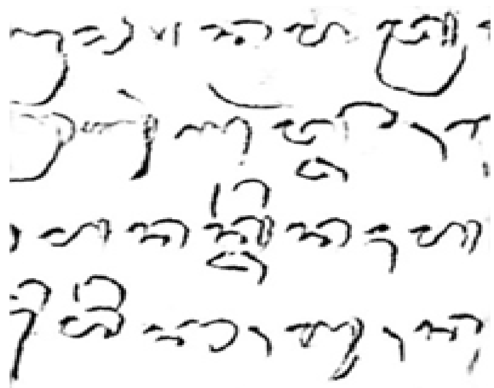
It is important to assess the effectiveness of the proposed U-Net model on a variety of benchmark datasets like H-DIBCO-2018 [16], AMADI_LONTARSET [17], PHIBD-2012[18] and our own HKHPL Dataset to assess its generalization ability and robustness. This will provide a comprehensive understanding of the model's performance and help to identify its strengths and weaknesses.Applying the proposed model on different benchmark datasets will also help to compare its performance with other state-of-art algorithms in this field and highlight its competitive advantages. The datasets used for the evaluation should cover a wide range of ancient document types and present various binarization challenges, such as variations in illumination, contrast, and degradation.

In addition, the results of the experiments on different benchmark datasets will provide insight into the scalability and applicability of the proposed model in real-world scenarios and help for further refinement and improve the model.It is crucial to choose the benchmark datasets carefully and perform a thorough evaluation of the model's performance to ensure that the results are reliable and representative of its actual capabilities.


(a)


(b)


(c)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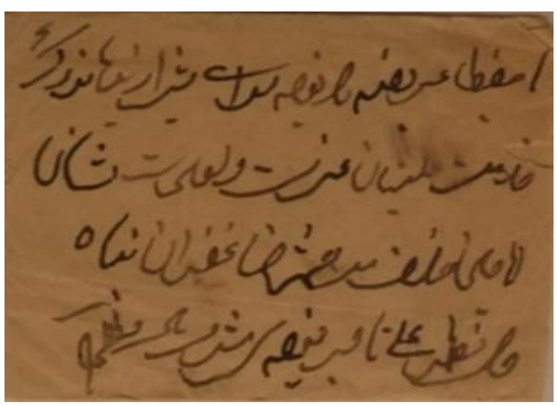
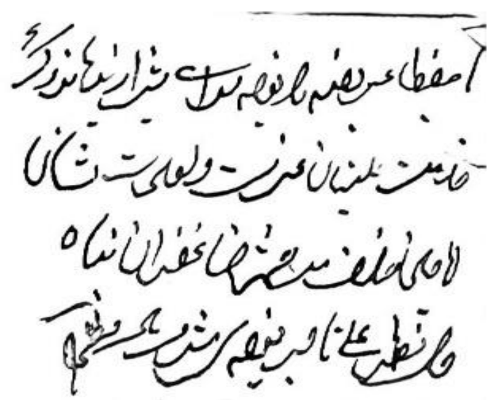
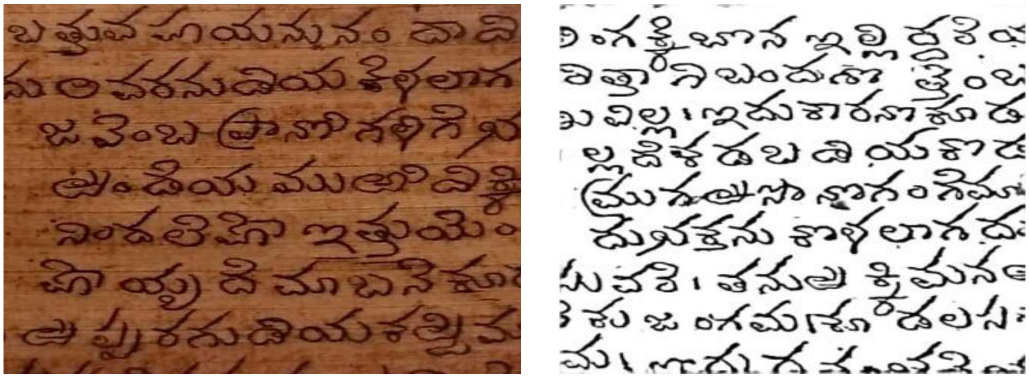

(e)


(f)



(g) (h)

Fig. 7. (a) Sample originalstandard H-DIBCO 2018image of dataset, (b) Proposed U-Net model appliedon standard H-DIBCO 2018dataset, (c) Sample originalstandard AMADI_LONTARSETimage of dataset, (d) Proposed U-Net modelappliedon standard AMADI_LONTARSET dataset (e) Sample originalstandard PHIBD 2012image of dataset, (f) Proposed U-Net model appliedon standard PHIBD 2012dataset, (g) Sample originalstandard HKHPL 2023 image of dataset, (h) Proposed U-Net model appliedon HKHPL 2023 dataset.

Table 2. Interpret about the F1-Measure value of existing dataset with proposed dataset.

Images	HDIBCO2018	AMADI LONTARSET	PHIBD 2012	HKHPL (Own dataset)
Image 1	36	21	33	35
Image2	29	23	26	39
Image3	17	20	31	42
Image4	26	20	19	43
Image5	27	20	20	42
Avg.	**27.0**	**20.8**	**25.8**	**40.2**

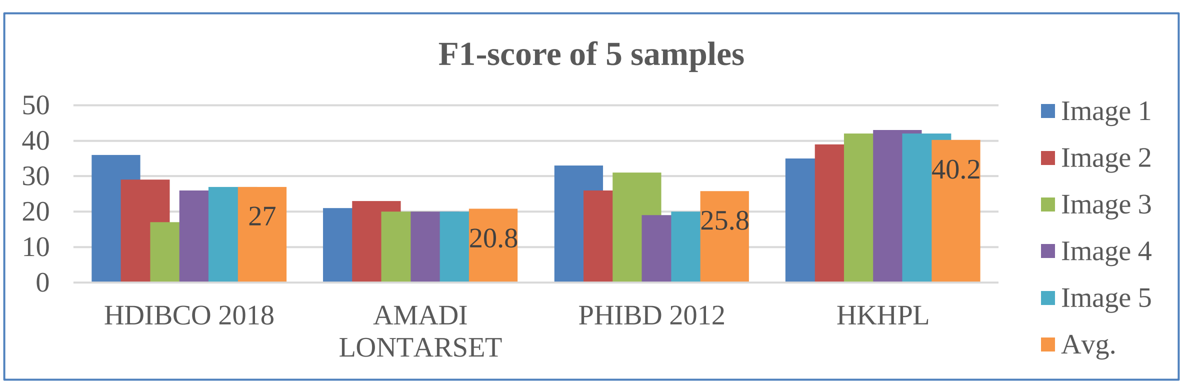
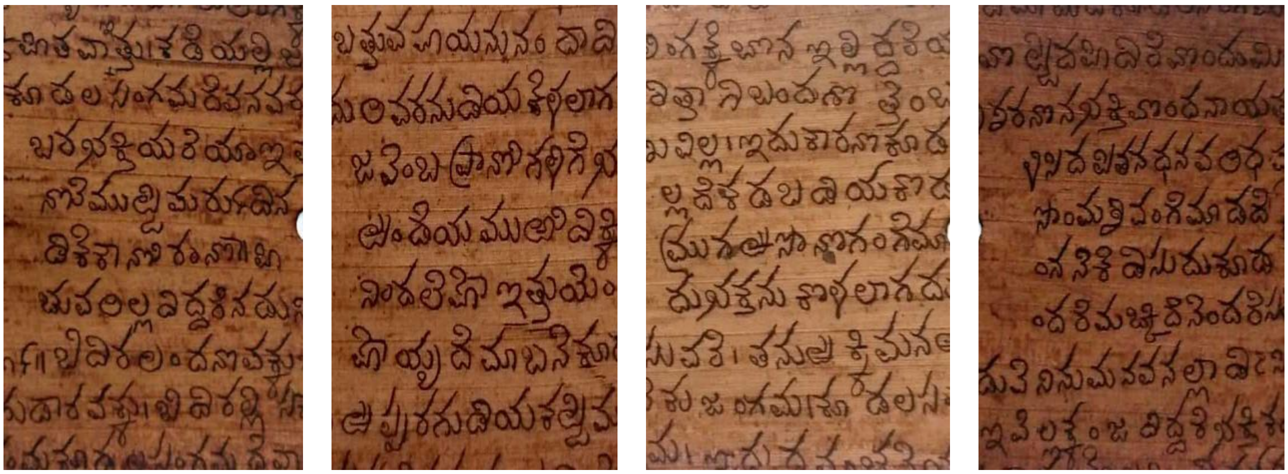


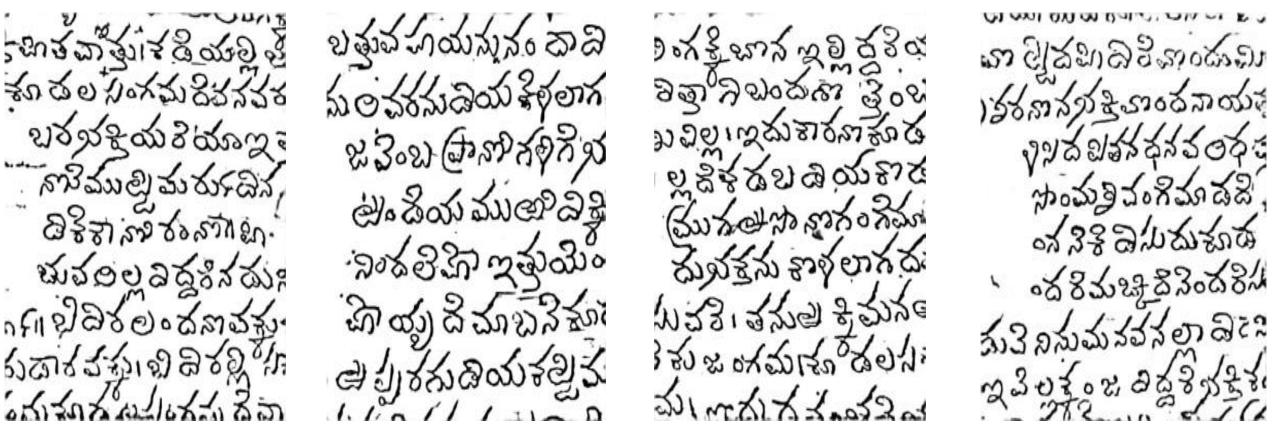
Fig. 8. Graphical representation ofthe F1-Measure value of existing dataset with proposed dataset

3.2 HKHPL Dataset (Own Dataset) results

The sample results of the U-Net model applied on HKHPL Dataset presented for visual comparison with the original handwritten Kannada document images Fig 9 (b) and the binarized images. The sample results should be visually appealing and easy to understand, with clear and concise explanations of the metrics used to assess the effectiveness of the U-Net model and classical binarization algorithms. This will help to communicate the results effectively to a wide audience, including researchers and practitioners in the field.



(a)



(b)

Fig 9. (a) Sample HKHPL Dataset original images, (b) Proposed U-Net model Applied our own HKHPL dataset image results.

4 Conclusion

The use of CNNs with U-Net architectures for ancient Kannada handwriting palm leaf binarization is a valuable tool that has the potential to improve the accurateness and effectiveness of the binarization process.This study provides a promising solution for the challenge of preserving and digitizing ancient Kannada handwritten on palm leaf.To assess the quality and effectiveness of the proposed technique. The performance measuring approaches; Precision, Recall, F-Measure, MSE and PSNR are used. In the literature, the higher the PSNR, Precision, F-Measure and lower the Recall and MSE determines the quality of the image. The promising results are achieved as compared to the other methods in the literature, namely; Souvola and Niblack. The proposed algorithm is also tested and implemented on other standard benchmark datasets, such as the HDIBCO2018, AMADI LONTARSET, PHIBD 2012 and our own HKHPL datasets and obtained positive resultsbased on F-measure27.01%, 20.8%, 25.8% and 40.2%respectively.

Acknowledgement

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