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Ancient Epic Manuscript Binarization and Classification Using False Color Spectralization and VGG-16 Model

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Abstract

Ancient Malayalam manuscripts include a vast quantity of materials, much of which pertains to ancient custom and culture. These manuscripts are the foundation of the rich and diverse culture that we possess today. The information extraction from such scripts written in “Thaliyola” or palm leaves would be an extensive and tedious task due to various challenges such as understanding the ancient script, damages generated due to miss-handling, stains and fungus and other environmental factors caused to the palm leaves. Preserving and segregating these documents through binarization and classification is an important task. Classification of these documents will lead to understanding unique ancient documents and preserving them for our current and future generations. In proposed work primarily an RGB image of the palm leaf document is given as input to the Spectral Angle Mapper(SAM) algorithm which takes the input and converts into RGB-A image with an additional Alpha channel, after FCC and TCC is calculated and a spectral image is generated which possess good text readability which is then followed by classification. The spectral model is passed to using VGG-16 model along with other binarized images, after training and testing achieved an accuracy of 90% on Jadakam and an accuracy of 85% with Bhagavatham.

Keywords: Malayalam; SAM; VGG-16; SPECTRALIZATION

1. INTRODUCTION

Palm leaves are one of the earliest materials used for writing. Thaliyola scripts are a critical source of information regarding our ancient past and history. These scriptures contain large information regarding not just events in history but also information regarding our rich culture. Since palm leaves degrade over time due to many external factors such as moisture, fungus etc. and get destroyed or have largely depreciated. Pre-processing has an important role while handling palm leaves due to the so mentioned factors. Manuscripts being a precious base of data should be protected. Classification and understanding of these documents with help for segregation of same category of knowledge present in palm leaf. Ancient texts in Malayalam can be classified based on content – There are multiple

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text documents and scriptures which can be ancient epics such as "Ramayana", "Bhagavatham" or an individual's horoscope "Jadakam". These documents might also contain information on astrology and epics which will be useful in present generation as well as future generations.

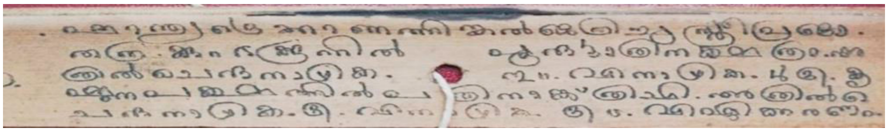

Fig 1: Jadakam palm leaf Image

Fig 2: Bhagavatham palm leaf Image

Modern hyperspectral imaging technologies generate massive datasets that have the ability to transmit a great deal of information; nevertheless, such a resource faces numerous obstacles in terms of data analysis and interpretation. Deep learning algorithms undoubtedly offer a wide range of possibilities for handling traditional imaging challenges as well as new and exciting problems in the spatial–spectral domain. Classification of ancient documents based on content with help of hyperspectral and structural components will make a huge difference in this area as ancient Malayalam scripts contain many similar looking and complex letters which makes it difficult to understand. Classification studies are carried out on hyperspectral images with machine learning processes will help in easy way of segregation of document as well as Spectralization will help to make the degraded document in readable format. The literature says there is no sufficient work to justify the spectral document classification. [1] Peng et al. (2016) discussed Text Classification using a deep model BLSTM-2DCNN on SST-1 and SST-2 datasets achieves 52.4% and 89.5% test accuracy. [2] Monir et al. (2019) experimented a supervised classification using a deep model CNN on 35,238 scientific articles and achieved 82% accuracy. [3] Imran Siddiqi et al (2009) discussed a machine learning classification model KNN on medieval manuscript images and got an accuracy of 94% .[4] R. Anil et al.(2015)investigated a method for Malayalam text classification using a deep model LeNet-5 on self-made dataset and got an average accuracy of 75% . [5] Fei Wang et al (2017) experimented on image classification using a de0ep model CNN on the CIFAR-10 and CIFAR-100 datasets to achieve an error rate of 3.90% and 20.45%. [6] Kamran Kowsari et al.(2017) discussed a machine learning combined classification model using Naive Bayes technique and SVM on WOS, IMDB datasets and achieved an accuracy of 86% overall. [7] Kalthoum et al (2017) proposed a combined machine learning Classification models using Gabor filter, LBP and KNN on Arabic manuscripts and achieved an accuracy of 86 percent. [8] Suganya et al (2017) discussed a serious of classifier like GSO, Firefly, CNN, J48, KNN, on Tamil inscriptions and achieved an accuracy of 93.33% on shapes. [9] Muhammad Zeshan Afzal et al. (2015) experimented a deep classifier CNN on Tobacco and image net datasets gives an accuracy of 77.6% and 68.25%. [10] Mohd Azlan Abu et al (2019) proposed an image classification model using DNN, MobileNet model on the ImageNet database and achieved up to 90% accuracy. [11] Surendra Pandurang Ramteke et al (2018) investigated a machine learning classifier SVM-ACS on Handwritten Marathi Text Document achieved an accuracy of 99.36 % . [12] Ghiassi et al (2012) proposed an Automated text classification system based on DAN2 on the Reuters-21578 dataset and achieved performance at P=0.05 level of significance. [13] Takeru Miyato et al.(2017) discussed a deep model Adversarial Training Methods for semi-supervised text classification on datasets IMDB,RCV1 etc. and got a test error rate of 16.6%. [14] J Krishnan et al(2021) proposed a Cross-Lingual Text Classification using a technique mBERT and XLM-R on transliterated language datasets and got improvement of

5.6% and 4.7%. [15] Mark Hughes et al(2017) discussed a deep model for text classification using CNN, Word2Vec on PubMed dataset and achieved an accuracy of 0.68. [16] Meduri Avadesh et al (2018) proposed a character recognition deep model CNN on a Sanskrit Database with 93.32% accuracy. [17] Bineesh Jose et al.,(2021) proposed a character recognition deep model CNN and ML model support vector machine were used and achieved an accuracy of 96.80%. [18] Neena K Pius et al. (2020) experimented on a method of character recognition using various deep models CNN, LeNet, ResNet and achieved Moderate results. [19] Xiao Huang et al.,(2020) experimented with Binarization of degraded document images with a deep models global-local UNets using DIBCO DATASET and got an improvement of 92.14%. [20] Dona Valy et al.,(2018) proposed a Character and Text Recognition system using various deep models CNN, LSTM-RNN on khmer palm leaf manuscripts to achieve an Error Rate of 2.40. [21] Dhanya Sudarsan et al.,(2018) experimented on Malayalam Palm leaf Manuscripts using a technique Contrast-Based Adaptive Binarization and achieved an accuracy level of 96.7% . [22] Amrutha Raj V et al.,(2017) proposed the techniques HOOSC, ANN on ancient grantha palm leaves and was able to achieve accuracy about 96.5%. [23] Asad et al.,(2017) proposed a Ink Mismatch Detection on UWA database using a technique Hysime in which Accuracy deteriorates highly. [24] Pratish Pushparaj et al.(2021) discussed deep models Convhs_5 and Resnet for reconstruction on the NTIRE 2020 dataset and got MAE 0.0110 and 0.0266. [25] Wenju Wang et al. (2021) proposed a framework for HSI reconstruction using DGCAMN on NTIRE 2020 dataset and Got RMSE of 0.0226 and MRAE of 0.0750 . [26] Mehta et al. (2020) discussed haze removal in images captured using HIDEGAN, R2HCycle on ICVL BGU, NTIRE 2020 datasets and got 28.04% improvement. [27] Akhtar et al.(2020) experimented on various techniques like HSI recovery from RGB using Gaussian Processes, Bayesian Inference on CAVE dataset and got 30.75% RMSE reduction.Y. [28] Fu et al. (2019) experimented a deep model CNN for HIS super resolution on the ICVL dataset and got RMSE of 0.9673Z. [29] Shi et al. (2018) proposed a model HSCNN on the NTIRE 2018 dataset and got MRAE improvement of 8.9% and 9.2%. [30] Bipin Nair BJ et al.,(2021) experimented a deep models CNN and Resnet for denoising Ancient Palm Leaf document and achieved an accuracy of 95.38%. [31] Bipin Nair BJ et al (2021) proposed a two phase machine learning model with buttorworth and otsus for denoising uneven illumination from ancient notebook images got an accuracy of 91.6. Some of the prominent literature is the given area is addressed in the below Table 1.

Table 1. Literature survey

Author	Methodology	Dataset	Challenges	Accuracy
Samir S. Yadav(2019)	CNN	chest X-rays,OCT	Dataset collection was difficult	93% Accuracy
Mohd Azlan Abu et al(2019)	DNN, MobileNet.	ImageNet Database.	In contrast to the large size of the training mode, the accuracy percentage is slightly low.	90% Accuracy
J Krishnan et al(2021)	mBERT-Joint-TS and XLM-R-Joint-TS	transliterated Hindi and Malayalam	Accuracy is low compared to training.	62.07% Accuracy on mBERT and 61.72% on XLM-R
Menghan Zhang(2021)	CNN, LSTM, and MLP	News Text	extract intriguing patterns from the text data was difficult	93.% Accuracy
Monir ech et al. (2019)	CNN	Web of science Dataset (35238 articles)	SVM classifier gave below average results.	82% Accuracy

2. Proposed Architecture

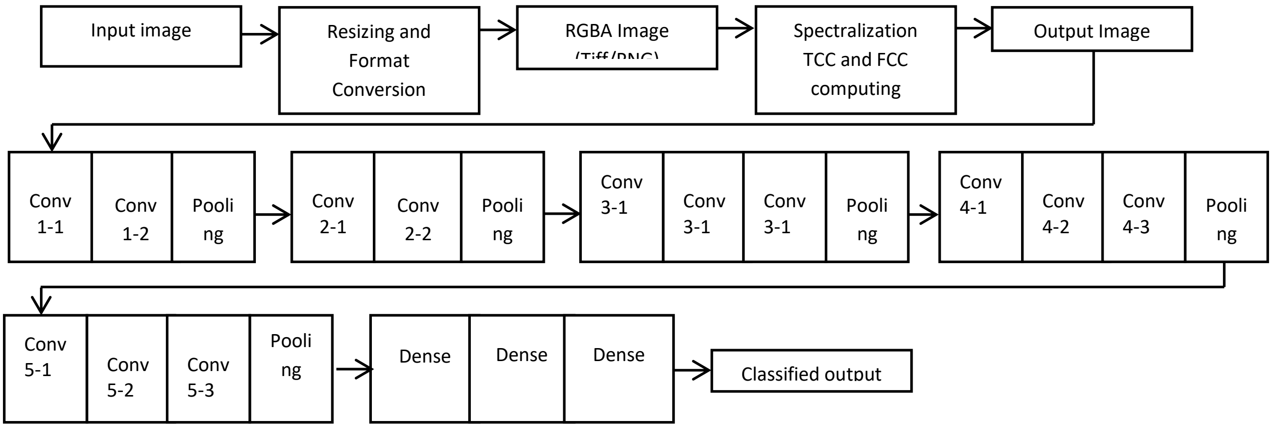

Fig. 3. Overall proposed system Architecture

Proposed architecture explains a series of process. First an Input RGB image is converted into an RGB-A which is a normalized image, adding another alpha channel to the input base RGB image helps in generating a pseudo spectral image, then a False color composition and True color composition are generated after which the reference pixel coordinates are also merged. This output from the Spectralization Algorithm is used for training and testing using VGG 16 model. this model has having total 16 layers. first two convolutional layers followed by one pooling layer then again 2 convolutional layers with one pooling layer after which comes 3 convolutional layer and a pooling layer further two more blocks with 3 convolutional layer and a poling layer finally three dense layers and an activation function which will help for classification of given input based on data.

2.1. Phase 1 – Spectralization

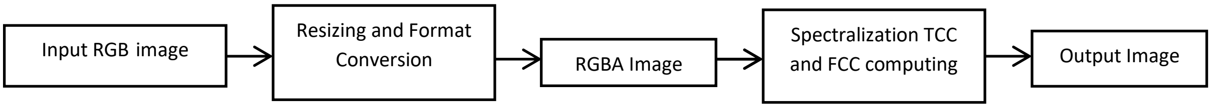

Fig. 4. Spectralization algorithm architecture

Fig.5 describes Spectralization in which RGB image is taken as input is converted into RGB-A having 4 number of channels of which the FCC and TCC is calculated and is stacked again as generated output. This spectral image is generated which is used by the classification model for training and testing in the later stages.

2.2. Phase 2 - Classification

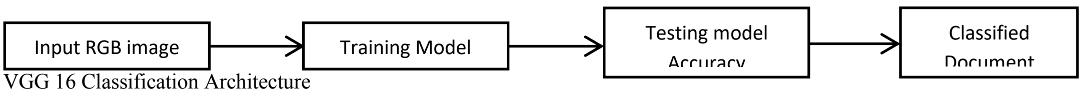

Fig. 5. VGG 16 Classification Architecture

Fig .6 explains about classification process here for training the model we are using Output of Spectralized and Binarized image. binarized image is developed as a Hybrid method (Using Savoula and Photoshop) is then categorized into two classes.

3. Mathematical model

3.1. Mathematical model for Phase 1

$$a = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\sqrt{\sum_{i=1}^{nb} t_i^2}\sqrt{\sum_{i=1}^{nb} r_i^2}}\right) \quad (1)$$

Here, nb: how many bands are there in the image, t: pixel spectrum, r: reference spectrum and alpha: spectral angle

3.2. Mathematical model for Phase 2

$$S(i,j) = \sum_m \sum_n I(m,n)k(i-m, j-n) \quad (2)$$

Mathematical model of the two-dimensional Convolution operation

$$w(x,y) \otimes f(x,y) = \sum_{s=-j}^{j} \sum_{t=-k}^{k} w(s,t) f(x-s, y-t) \quad (3)$$

Activation function (ReLu) helps in introducing non linearity for the model

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (4)$$

σ Stands for softmax, $\vec{z}$ Stands for input vector, e^{z_i} stands for standard exponential function for input vector, K stands for number of classes in the multi-class classifier, e^{z_j} stands for standard exponential function for output vector

Activation function (SoftMax)

$$E[g^2]_t = \beta E[g^2]_{t-1} + (1-\beta)\left(\frac{\delta C}{\delta w}\right)^2$$
$$w_t = w_{t-1} - \frac{\eta}{\sqrt{E[g^2]}}\frac{\delta C}{\delta w} \quad (5)$$

E[g] — moving average of squared gradients. dC/dw — gradient of the cost function with respect to the weight. n — learning rate. Beta — moving average parameter (good default value — 0.9)

4. Pseudo Code for Spectralization and classification

Input I_{RGB} – Resize (I_{RGB})
I_{RGB} – I_{RGBA}
I_{RGBA} – I_R I_G I_B I_A
Normalize (I_R, I_G, I_B, I_A)
($I_R + I_G + I_B + I_A$) stack = I_{ISP}
I_{ISP} – Resize (I_{ISP})
I_{ISP} – VGG (Training)
(VGG)Testing – C- D

Spectral Algorithm first Reads the image with band I_{RGB} – Input RGB and is then Resizes it hence Resize I_{RGB}. Alpha channel is added to I_{RGB} – giving I_{RGBA}. Then the algorithm reads the grid values into numpy arrays and normalizes them Normalize I_R, I_G, I_B, I_A further it is stacked $I_R + I_G + I_B + I_A$ to create True Color Composition and the False Color Composition. Finally I_{ISP} - Spectral Equivalent of the RGB input image I_{RGB}, I_{ISP} is generated. I_{ISP} is Resized and is Given for VGG Training. Then after defining the number of epochs and batch size bottleneck features are loaded which was saved earlier. Based on the class labels for the training data we get the bottleneck prediction from the pre-trained VGG16 model to predict the final classification VGG Testing and C- D represents Classified Document

5. Results and Discussion

5.1. Spectral Result

Fig.8 is the Input image Jadakam which is given to the Spectralization algorithm that which generates the Spectral output Fig.9. Fig.10 is the Input image of Bhagavatham which is given to the Spectralization algorithm which generates the output Fig.11.

Phase 1 Experimental Result

Input image of Jadakam

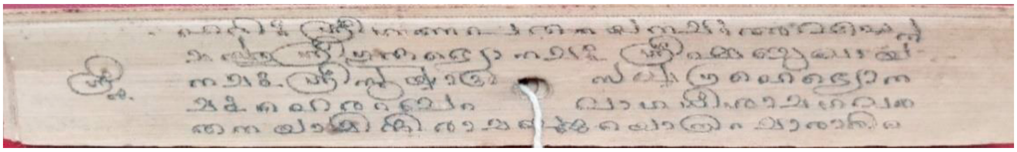

Fig.6: Jadakam Input image given to the Spectralization algorithm

Output result

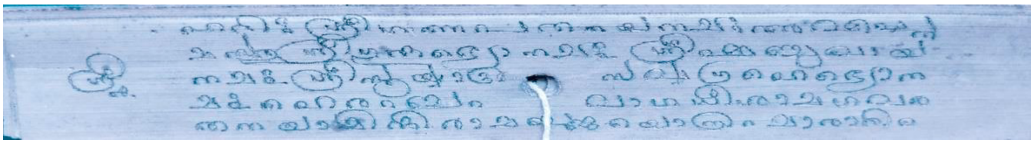

Fig.7: Result of given input Jadakam

Input image of Bhagavatam

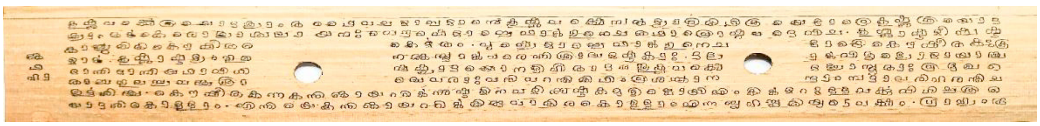

Fig.8: Bhagavatham input image given for the Spectralization algorithm

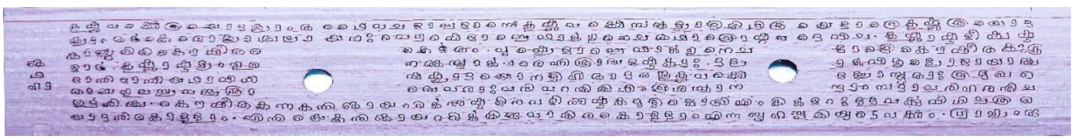

Fig.9: Result of given input Bhagavatham

Output result

5.2. Classification Result

Fig 10 and Fig 11 are given as input for the classification where the model has predicted Fig.10 Correctly as Jadakam with an accuracy of 90% and Fig.11 as Bhagavatham with an accuracy of 85%

Phase 2 Classification Result

Input : Jadakam Image

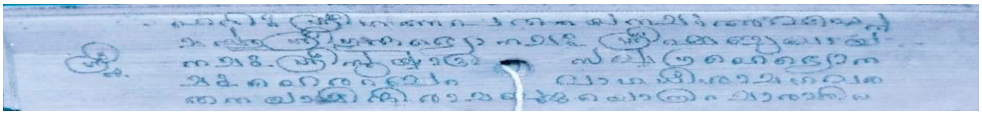

Fig.10: Jadakam image give input to the classification model

Classification result

```
Label: JADAKAM
Accuracy: {} 0.9090909361839294
```

Input: Bhagavatham Image

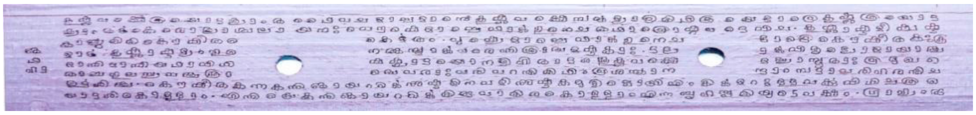

Fig.11: Bhagavatham image given input to classification model

```
Label: BHAGAVATAM
Accuracy: {} 0.8535353541374207
```

6. Perfomance Evalutation

6.1. RGB classification confusion matrix

Table 2: RGB classification confusion matrix

		PREDICTED	
ACTUAL		Bhagavatham	Jadakam
	Bhagavatham	44	3
	Jadakam	2	29
	Total for Class	46	32

Table 2 contains the confusion matrix of the RGB classification a total of 73 images were predicted correctly out of 78 Images. 44 images out of 46 from Bhagavatham class were predicted correctly and 29 Images of 32 from Jadakam dataset were also able to be classified correctly.

6.2. RGB classification confusion matrix

Table 3: Spectral classification confusion matrix

		PREDICTED	
		Bhagavatham	Jadakam
ACTUAL	Bhagavatham	45	2
	Jadakam	1	30
	Total for Class	46	32

Table 3 contains the confusion matrix of the Spectral classification a total of 76 images were predicted correctly out of 78 Images. 46 images out of 46 from Bhagavatham were predicted correctly, 30 Images from 32 of Jadakam were also able to be predicated into the correct class label.

6.3 Performance Evaluation metrics of the original image classification:

Table 4: Table with performance evaluation metrics of RGB model

Class	Accuracy	Precision	Recall/ Sensitivity	Specificity	F1 score
Bhagavatham	93.58	93.61	95.65	90.62	94.62
Jadakam	93.58	93.54	90.62	95.65	92.06

Table 4 describes RGB model achieved an accuracy of 93% for Bhagavatham and 93% accuracy for Jadakam with a Precision of 93% and 93% respectively for Bhagavatham and Jadakam. Recall of 95% for Bhagavatham and 90% for Jadakam. Specificity was 90% for Bhagavatham and 95% for Jadakam also an F1 score of 94% for Bhagavatham and 92% for Jadakam

6.4 Performance Evaluation metrics of the spectral classification:

Table 5: Table of performance evaluation metric of Spectral model

Class	Accuracy	Precision	Recall / Sensitivity	Specificity	F1 score
Bhagavatham	97.43	95.83	100	93.75	97.87
Jadakam	97.43	100	93.75	100	96.77

Table 5 describes about Spectral model achieved an accuracy of 97% for Bhagavatham and 97% accuracy for Jadakam with a Precision of 95% and 100% respectively for Bhagavatham and Jadakam. Recall of 100% for Bhagavatham and 93% for Jadakam. Specificity was 93% for Bhagavatham and 100% for Jadakam also an F1 score of 97% for Bhagavatham and 96% for Jadakam. comparatively more accuracy getting from Bhagavatham documents for classification. the Fig12-fig16 interprets a graph having X axis shows the batch sizes and the Y axis shows the accuracy. Epoch for each graph is fixed thus showing the relation between batch size and accuracy at various epochs. Was able to achieve good results at 30 Epochs and 25 as Batch size

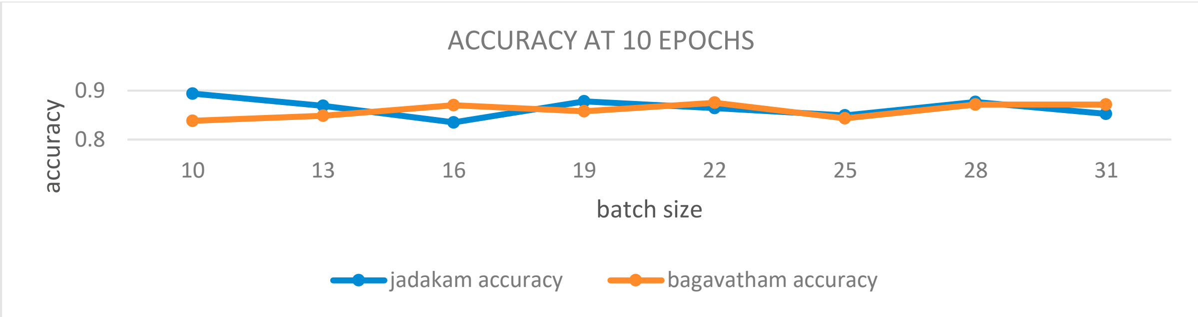

Fig.12: Accuracy with Various batch sizes at 10 epochs

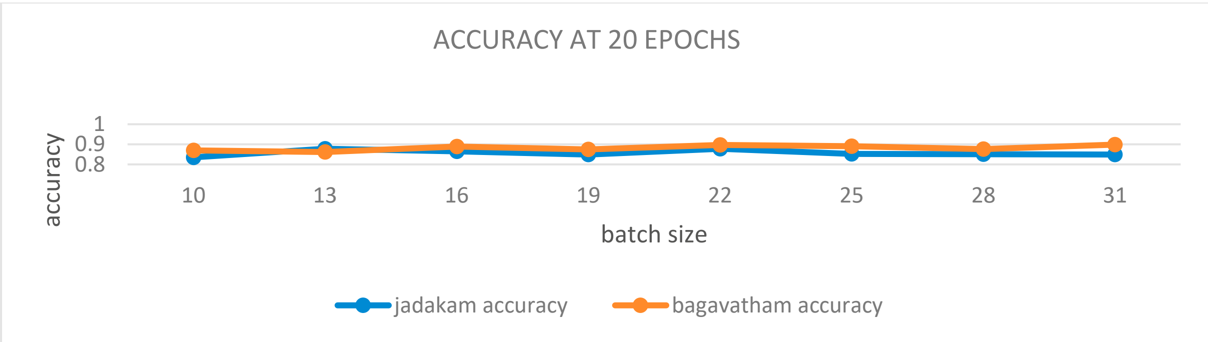

Fig.13: Accuracy with Various batch sizes at 20 epochs

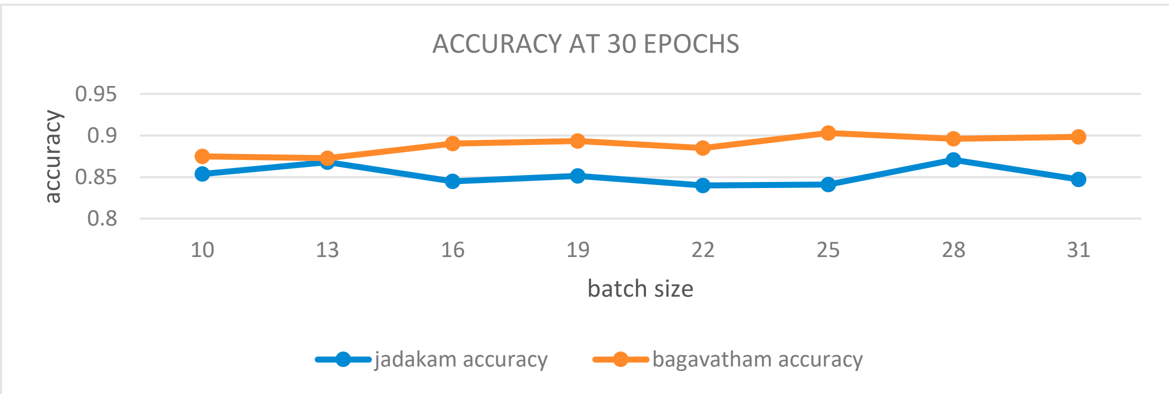

Fig.14: Accuracy with Various batch sizes at 30 epochs

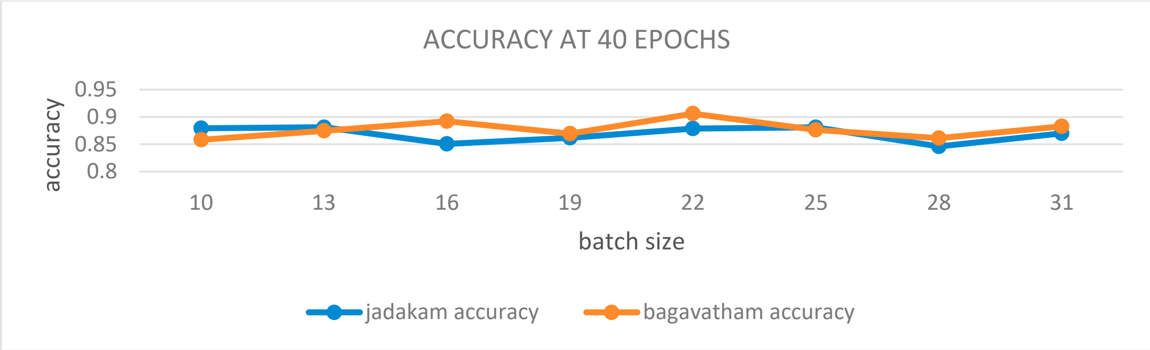

Fig.15: Accuracy with Various batch sizes at 40 epochs

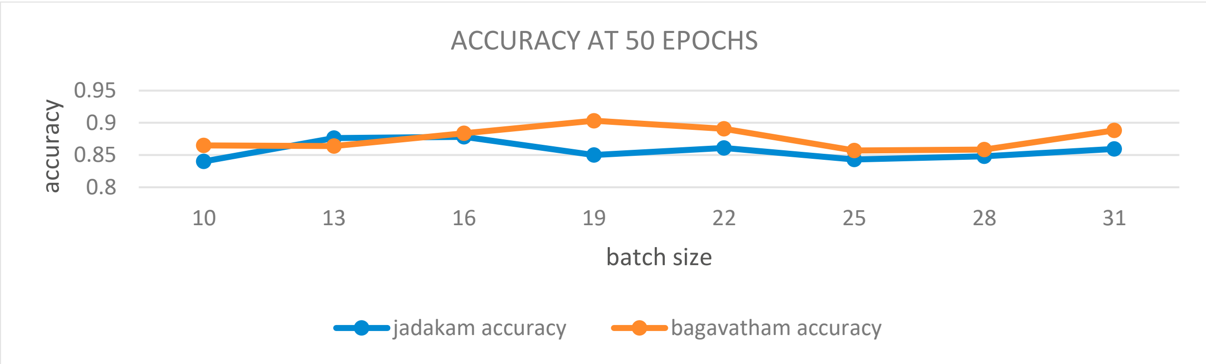

Fig.16. Accuracy with Various batch sizes at 50 epochs

Table 6: Table of Accuracy Comparison RGB dataset and Spectral Dataset

JADAKAM			BHAGAVATAM	
Epochs	Accuracy RGB	Accuracy Spectral	Accuracy RGB	Accuracy Spectral
10	0.790576379	0.852544	0.800858666	0.871441
20	0.78379648	0.835136	0.783081627	0.870405
30	0.818296015	0.8471	0.782904128	0.8982
35	0.779989355	0.863838	0.811601072	0.881668
40	0.803756992	0.859497	0.783582183	0.888464
45	0.791083605	0.845815	0.793630635	0.893721
50	0.804128455	0.869776	0.805900871	0.88289
Average :	0.795946754	0.853386571	0.794508454	0.883827

Table 6 shows the average and total average accuracy of the RGB and Spectral Classification of both Jadakam and Bhagavatham where for Jadakam it is 79 % for RGB classification compared to 85% for the spectral Classification and for Bhagavatham it Is 79% .

Table 7: Table with accuracy at various epoch and batch size of proposed work

		JADAKAM	BHAGAVATAM
Batch Size	Epochs	Average Accuracy	Average Accuracy
10,13,16,19,22,25,28,31	10	0.864854	0.859475
10,13,16,19,22,25,28,31	20	0.857048	0.88216
10,13,16,19,22,25,28,31	30	0.852017	0.889118
10,13,16,19,22,25,28,31	35	0.8578	0.885444
10,13,16,19,22,25,28,31	40	0.857091	0.876375
10,13,16,19,22,25,28,31	45	0.863548	0.881655
10,13,16,19,22,25,28,31	50	0.868557	0.877687

Table 7 shows the average accuracy at various epochs 10 to 50 with different batch sizes ranging from 10 to 31 batch size. Highest accuracy of classification we are getting for 30 epochs with an average batch size 20.

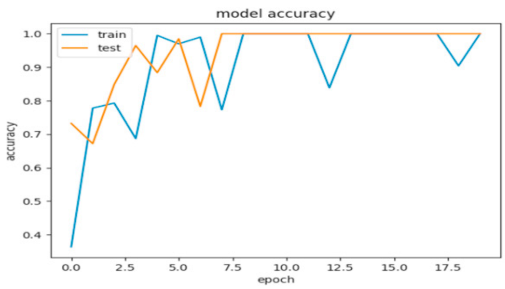

Fig.17: Overall model accuracy graph

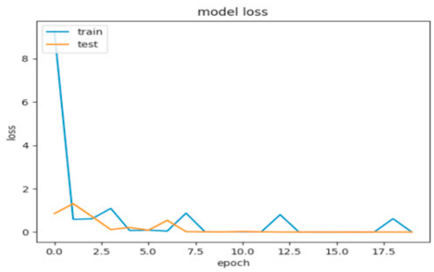

Fig.18: Overall model loss graph

In the above Fig.17 depicts a graph shows the overall model accuracy where in x axis interprets the number of epochs and in the y axis interprets accuracy. Second Graph Fig.18 shows the overall loss at various epochs in x axis represents the number of epochs and y axis represents the loss.

7. Conclusion

Palm leaf documents are one of the oldest forms of recorded data which contains information from various areas such as our history and medicine,astrology, epics etc. Digitization and saving of these data still remains an important factor in todays modern world. In our work we have attempted to do a spectral classification of the palm leaf document using spectral analysis which is novel in the area of document classification, to make the document in more readable format. Lack of actual spectral palm leaf document datasets captured using industrial spectral camera is one of the main limitations, so we had to go with an alternative approach of generating fake spectral data from RGB images. Our proposed work showcases ancient malayalam manuscript document classification using spectral analysis. It utelises the appropriate functionality of a spectralization model, Spectral Angle Mapper(SAM) to obtain a Spectral Cube after the calculation of True color composition and False color composition. after training and testing we achieved an accuracy of 90% with Jadakam and an accuracy of 85% with Bhagavatham. For future works more datasets can be incorporated and accuracy can be improved.

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