REKAYASA
Journal of Science and Technology
https://journal.trunojoyo.ac.id/rekayasa

REKAYASA, 2024; 17(1), p.175-185
ISSN: 0216-9495 (Print)
ISSN: 2502-5325 (Online)

Convolutional Autoencoder for Reconstruction of Historical Document Images: Ancient Manuscript Babad Lombok

(*Convolutional Autoencoder* untuk Rekontruksi Citra Dokumen Sejarah: Naskah Kuno Babad Lombok)

Fahmi Syuhada[1*], Asno Azzawagama Firdaus[2], Ana Tsalitsatun Ni'mah[3], Yuan Sa'adatai[4], Muhammad Tajuddin[5]

[1,2,4]Ilmu Komputer Universitas Qamarul Huda Badaruddin Bagu
Jl. H. Badruddin, Bagu Praya Lombok Tengah, 83371, Indonesia

[3]Pendidikan Informatika, Universitas Trunojoyo Madura
Jl. Raya Telang - Kamal Bangkalan, 69162, Indonesia

[5]Ilmu Komputer, Universitas Bumi Gora
Jl. Ismail Marzuki, Cilinaya, Cakranegara, Mataram, 83127, Indonesia

*corresponding author: fahmisy@uniqhba.ac.id

DOI: https://doi.org/10.21107/rekayasa.v17i1.26101

ABSTRACT

The Babad Lombok is an ancient literary or manuscripts document that generally contains stories about the origins of the people of Lombok. This document is written on a lontar leaf, which in the past was used to write manuscripts, letters, and documents. At present, the Babad Lombok document can be seen in the form of photos or scans, so it can be viewed without having to go to a museum or cultural heritage site where the document is usually exhibited. However, because this document is an ancient artifact that has been around for hundreds of years, it has naturally experienced fading in the original document or its scanned versions. This makes the text inside less clear. This paper proposes to automatically reconstruct/repair the Babad Lombok document using a neural network. The type of neural network used is an Autoencoder or Convolutional Autoencoder (CAE). The CAE model is built sequentially and trained using original images of Babad Lombok as its training data and manually corrected images of Babad Lombok as the target or ground truth data. In the process, the two types of data are iteratively cropped to a size of 64x64 along the original size of the Babad Lombok image. This process results in input and target data for the CAE training process in this research, each consisting of 48,288 images. Testing the trained autoencoder model shows that the Babad images have been successfully repaired, making the text quality clearer before reconstruction. Ultimately, the proposed CAE has achieved training and validation accuracies of 89.09% and 94.57%, with corresponding loss values of 0.0418 and 0.0226.

Keywords : Ancient, Manuscripts, Lombok, Reconstruction, Convolutional, Autoencoder

ABSTRAK

Babad Lombok merupakan dokumen sastra kuno yang umumnya berisi tentang cerita asal muasal masyarakat Lombok. Dokumen ini dituliskan dalam sebuah daun lontar dimana jaman dahulu daun ini digunakan untuk menulis naskah, surat, dan dokumen. Saat ini dokumen babad lombok sudah dapat dilihat dalam bentuk dokumen hasil foto atau pemindaian sehingga dapat di lihat tanpa harus pergi ke museum atau cagar budaya tempat dokumen ini biasa dipamerkan. Namun dikarenakan dokumen ini merupakan barang bersajarah yang sudah ada serratus tahun lebih tentu mengalami pemudaran pada dokumen asli atau hasil pemindaiannya. Hal ini tentu membuat tulisan di dalamnya menjadi kurang jelas. Pada paper ini mengusulkan untuk melakukan rekontruksi/perbaikan secara otomatis pada dokumen Babad Lombok menggunakan *neural network*. Jenis *neural network* yang digunakan yaitu *Autoencoder* atau *Convolutional Autoencoder* (CAE). Model CAE dibuat secara sequensial yang dilatih menggunakan data gambar babad lombok asli sebagai data latihnya dan gambar babad lombok yang sudah diperbaiki secara manual sebagai data target atau ground truth. Pada prosesnya dua jenis data tersebut dipotong dengan ukuran 64x64 secara iterasi sepanjang ukuran asli citra Babad Lombok. Proses tersebut menghasilkan data input dan target untuk proses pelatihan CAE pada penelitian ini masing-masing 48.288 citra. Pengujian model *autoencoder* yang sudah dilatih menunjukkan bahwa citra babad berhasil diperbaiki sehingga kualitas tulisan yang terdapat didalamnya tampak lebih jelas sebelum rekontruksi. Pada akhirnya CAE yang diusulkan telah mencapai akurasi pelatihan dan validasi sebesar 89,09 % dan 94,57 % dengan nilai loss masing-masing 0.0418 dan 0.0226.

Kata kunci: Naskah, Kuno, Babad, Rekontruksi, Convolutional, Autoencoder

INTRODUCTION

Babad Lombok (Figure 1) is an ancient literary document that generally contains the story of the origin of the people of Lombok. Babad Lombok contains the origin of the Sasak people in Lombok and their historical journey to establish the kingdom. Then the spread of Islam in Lombok and finally the fall of the Selaparang kingdom to the Balinese king (Mintosih, Lestarining, and others 1999). This document was written on a palm leaf which in the past was used to write manuscripts, letters and documents. Nowadays, Babad Lombok documents can already be seen in the form of photographed or scanned documents so that they can be viewed without having to go to museums or cultural heritage where these documents are usually exhibited.

Fumigation activities were carried out to keep the manuscript preserved. The dry nature of palm leaves means that these manuscripts need extra care so that they do not deteriorate over time. The digitization of the lontar manuscript of the Lombok babad is a form of preservation so that it can be documented without being affected by the condition of the babad material. In addition, the Millennial generation, especially in Lombok, can enjoy the lontar babad lombok using current technology. Digitization is done by scanning or digital cameras and stored in an image format that is accessed through a computer (Tajuddin et al. 2019).

However, because this document is a historical item that is over a hundred years old, there is certainly fading in the original document or the scans. This makes the writing in it less clear. Improvements to the quality of the writing contained in the babad lombok document need to be made as an effort so that the writing can be read more clearly. The results can be used as a medium to study the content written in it or for further research.

Improving the writing on the chronicle of Lombok is a research challenge by utilizing current technology. Digital image processing is a research topic that can be done to do this. As carried out by Tajuddin et al 2021 where the Transformation of Lontar Babad Lombok Towards Digitization Based on Natural Gradient Flexible (NGF) (Muhammad Tajuddin Anwar, Syahroni Hidayat 2021). The algorithm used implements a Gaussian density model on the gradient structure to ensure source distribution and is able to process mixed data containing super Gaussian and subGaussian source signals (Sreedevi et al. 2013).

Until now, there has not been too much research focusing on the image of Babad Lombok. However, if traced with other studies, the condition of the image of Babad Lombok is similar to the image of other historical documents that have been studied by many researchers. Document analysis, preservation, restoration and reconstruction in the field of cultural heritage studies have evolved over the past few decades. Researchers have applied a wide variety of methodologies with advances in multimedia technology to preserve ancient handwritten manuscripts. The goal is how to restore or repair images on historical documents so that the writing contained therein appears clear and tries to eliminate noise or disturbances contained therein.

Restoration or repair of historical document images is a challenge in the low-level vision variant which deals with image features such as edges, contours, etc (Freeman, Pasztor, and Carmichael 2000). Extensive studies have been conducted to restore damaged historical documents and extract important information from them. Various types of image noise reduction algorithms and other relevant techniques have been applied over time to solve this classic problem of historical document image restoration (Mallik et al. 2017). The type of improvement that will be carried out on the image of Babad Lombok is the removal of the noise contained therein which causes the writing

Figure 1 An example of a piece of document from Babad Lombok

to become unclear. Various denoising filter techniques have been developed to remove noise from media images, Gaussian, and bilateral filters (Rama Lakshmi et al. 2023; Sehgal and Kaushik 2022; You et al. 2023). Some recent approaches are the use of Neural Network - Deep Learning used for noise in an image (Kaur, Karmakar, and Imran 2023).

Deep Neural Network (DNN) is a recent research trend that has superior performance compared to traditional image denoising or enhancement algorithms in computer vision (LeCun, Bengio, and Hinton 2015). Impressive advances and developments in deep learning architectures have provided new approaches with successful applications in pattern recognition, image and signal processing, speech recognition, natural language processing (NLP), big data analysis, information retrieval, computer vision, and image analysis (W. Liu et al. 2017). Convolutional Neural Network (CNN) has great performance in image processing and problem solving of computer vision topics. One of the types discussed in this paper is the Convolutional Autoenoder (CAE) which is widely used in the image enhancement process. Autoencoder is a type of neural network architecture to repair noise in an image. Autoencoder has the same input and output dimensions which will be modeled for image enhancement process.

This paper proposes the implementation of the use of convolution autoencoder (CAE) in the restoration or repair of the image of Babad Lombok. The goal is to make the writing contained therein appear clearer than the background. The autoencoder architecture model is designed and trained using the data of Babad Lombok image which is manually repaired by human. The proposed Fully Convolution Autoencoder architecture consists of multiple convolution layers as well as multiple deconvolution layers. The network model cleans and reconstructs and repairs the written content contained in the Babad Lombok image without losing the written content in it.

LITERATURE REVIEW

Studies on preservation, restoration, reconstruction or repair and other topics in the field of digital image processing and computer vision on the image of Babad Lombok are not widely carried out Tajuddin et al, (Muhammad Tajuddin Anwar, Syahroni Hidayat 2021) conducted a study related to the Transformation of Lontar Babad Lombok Towards Digitization Based on Natural Gradient Flexible (NGF). The application of the NGF-ICA algorithm is carried out to improve image quality which is assessed based on the evaluation parameters MSE, PSNR, SSIM and Entropy improvement. The focus of the repair carried out in this study is the repair of damage that is quite severe both the edges and the writing area.

Babad Lombok is a historical document that generally has the same characteristics as other historical heritage documents. The factor that occurs is that historical documents are objects that have a long age so that aging occurs and causes the appearance of noise so that the writing contained becomes less clear. Several studies present several image processing and computer vision algorithms and techniques. In general, document binarization is one of the most popular steps for document retrieval techniques (Dixit and Shirdhonkar 2015; Mallik et al. 2017). Otsu is the most standard binarization algorithm in image processing and computer vision (Otsu and others 1975). Until the last few decades, there have been many studies on binarization algorithms that can be grouped into several categories, namely Global Threshold, Local Threshold, Edge Based, Image Transform, Mixture model, CRF, and Deep Learning (Tensmeyer and Martinez 2020).

The research topic Deep Neural Network (DNN) is a recent research trend that has superior performance compared to traditional image denoising or enhancement algorithms in computer vision (Wang and Deng 2021). Deep learning has provided powerful new approaches in pattern recognition, image and signal processing, speech recognition, natural language processing (NLP), big data analysis, information retrieval, computer vision, and image analysis (W. Liu et al. 2017). Convolutional Neural Network (CNN) has great performance in image processing and problem solving of computer vision topics.

Autoencoder is a CNN-enhanced method that can be used in image denoising and restoration (Mao, Shen, and Yang 2016). Autoencoder is very useful in the field of unsupervised learning where it is basically used for data compression and dimension reduction (Hinton, Krizhevsky, and Wang 2011). This neural network is designed to reconstruct the input image. Figure 2 is an architectural model of the autoencoder where the input image will enter the encoding phase to reduce the dimensions and return it back in the decoding phase which is the result of its reconstruction. Encoding, Bottleneck and Decoding is the basic structure of autoencoder.

The encoder is the part for dimension reduction and feature extraction that is composed of hidden layers of a neural network containing a smaller number of nodes than the input layer. Bottleneck is a lower dimensional hidden layer where the encoding is produced. The bottleneck layer has a smaller number of nodes and the number of nodes in the bottleneck layer also gives the dimension of the input coding. The decoder reconstructs a clean version of the image based on the features learned by the encoder layers.

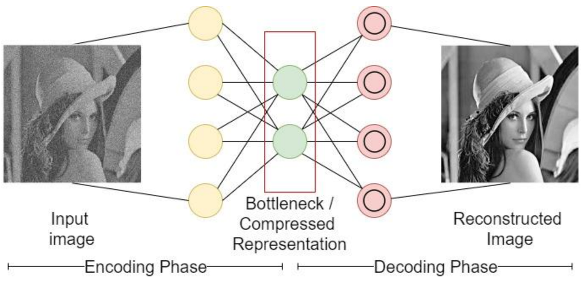


Figure 2 Autoencoder architecture for reconstruction or repair of Babat Lombok images

The development of autoencoder methods has been carried out in various studies such as data compression (T. Liu et al. 2021), face recognition (Hammouche et al. 2022), feature extraction (Parida and Bhoi 2018), image reconstruction (An and Cho 2015), and noise recognition (Yasenko, Klyatchenko, and Tarasenko-Klyatchenko 2020). A similar case to the purpose of this paper is the autoencoder which studies the restoration of historical document images that are very fragile and easily degraded. The auto coder is trained to be able to recognize the input image of the historical document to be able to recognize the repair image / ground truth. Based on the test results, the trained auto coder can reconstruct the image from its input, resulting in a new image of the historical document that has been repaired with noise and the writing contained therein as well as some disturbing features in it (Raha and Chanda n.d.).

RESEARCH METHODS

This section discusses how the proposed method or technique. This research develops a Convolutional Neural Network (CNN) Autoencoder model to perform the task of repairing images of Lombok chronicles. CNN is very popular in the field of artificial intelligence computer vision which is commonly used in classification. Convolutional Autoencoder is the development of CNN models to perform image reconstruction or repair. In general, the way of training CNN classification and image repair is the same as Autoencoder. In the classification of the input image is entered and trained so that it can recognize the label as the output. The difference is that the output label in the repair process is a ground truth image that has the same dimensions as the reconstruction target. The ground truth image can be created manually with human help.

Figure 3 is the design of the training architecture of the Lombok Babad image reconstruction/repair technique model using the Convolutional Autoencoder (CAE) method. CAE was developed and trained to be able to receive input in the form of pieces of the image of Babad Lombok and reconstruct it based on the Ground Truth image. Iteration of 64x64 pixels image slice is done as long as the size of the original image of babad lombok and ground truth is done. The CAE network uses convolutional network to transform the high dimensional feature map that represents the prominent and dominant information in the input image. Then the clean input is obtained from the deconvolutional layer reconstruction (Raha and Chanda n.d.). In the training process, the CAE model is taught to try to synthesize a reconstructed image until it is similar to the given ground truth image. The CAE network architecture proposed in this paper consists of 3 convolutional layers in the encoder and 5 deconvolutional layers in the decoder.

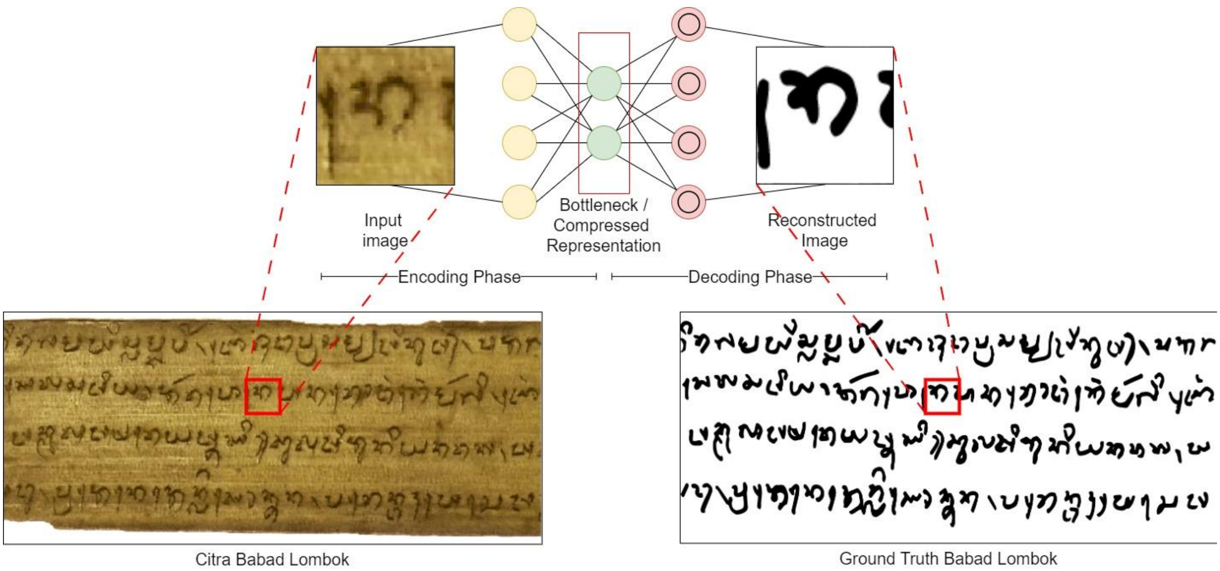


Figure 4 Training technique model for image reconstruction/repair of Babad Lombok with CAE

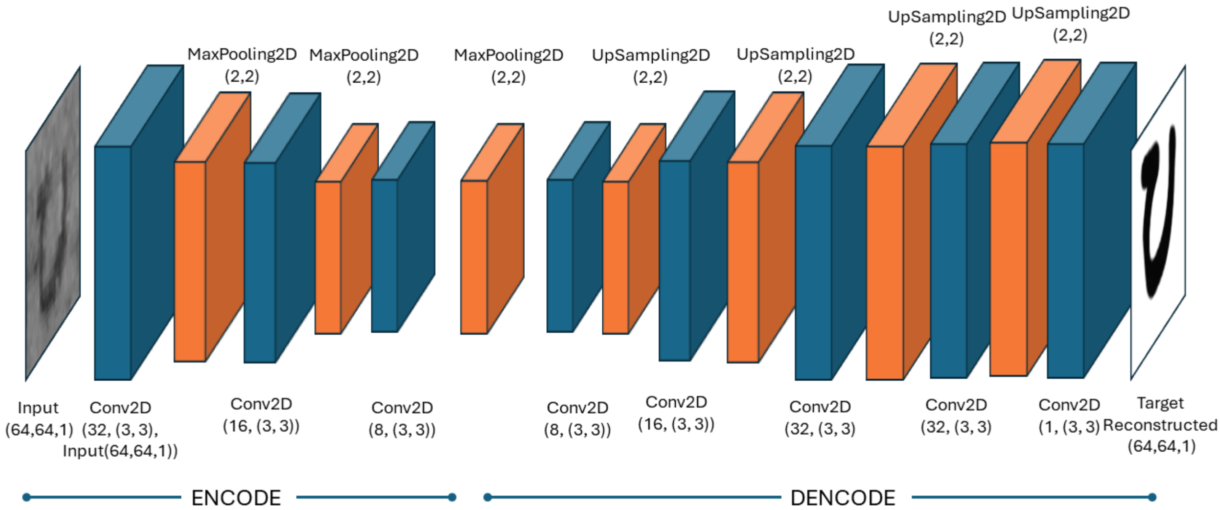


Figure 3 CAE architecture details to reconstruct or repair the input image of the Lombok Babad piece based on the target or ground truth

Rectified Linear Unit (ReLU) is used as the non-linear activation function in each layer.

CAE is designed to accept input grayscale image of dimension (64, 64, 1) and reconstruct it with the same dimension as the reconstructed image. In the encode section, each convolution layer is separated by a maxpooling layer to reduce the dimension as a feature search. While in the docoder section, the deconvolution layer is separated from the UpSampling layer to reconstruct the dimensions of the compressed image that produces the target image. Figure 4 is the complete architecture of the CAE proposed in this research for training and testing image reconstruction.

RESULTS AND DISCUSSION

This research was conducted using Python by implementing the Keras Tensorflow library designed using the Jupyter-Lab application. The machine specifications used to design a CAE network are Core I5 Processor with 8GB RAM. Furthermore, this section presents a description of the experiments and research results conducted on the method proposed in this paper.

A. Dataset

In this paper, the data used is the ancient manuscript data of Babad Lombok which has been scanned into a digital file (Tajuddin n.d.). The data has started to be used in previous research that discusses image retouching which focuses on the edge retouching of the Babad Lombok palm document [3]. There are two types of data sets needed in this research, especially in the CAE model training process as shown in Figure 3. The data sets are the input image of Babad Lombok and its ground truth image. The input image is the original image of Babad Lombok which is converted into a gray image. While the ground truth image is the target image where the CAE model is trained to be able to reconstruct or repair the input image like this target image. The Ground Truth was created by manually tracing the original image on printed paper with human assistance. The result of the tracing is then converted into a digital file whose position will be equalized with the original image.

Figure 4 is a sample of the original digital image of Babad Lombok. In the research process, each image is divided into 4 parts with a size of 1284x555. Each of these divisions is used for the plagiarism process so as to make the ground truth clearly visible. The image that has been divided will be cut 64x64 sequentially from the pixel coordinate (0,0) where horizontally is done with a flicker of 10 pixels and vertically is done with a multiple of 5 pixels. In the end, the input image and the ground truth that are included in the CAE model are 48,288 pieces of image each.

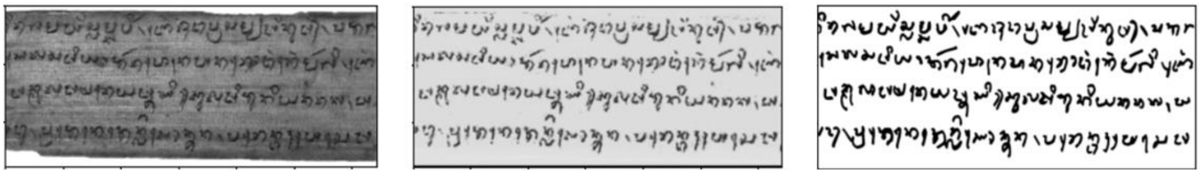
B. CAE Model Training

The architecture of the CAE model designed in this research looks like Figure 4 where the input image of Babad Lombok data is trained to reconstruct a new image based on the ground truth. The CAE model is implemented using the Keras Tensorflow library which is formed sequentially. The first convolution layer is set to accept the input of Babad Lombok data slice with dimension (64,64) with single layer type or grayscale image. In the encoder part of the CAE, the maxpooling layer is used to reduce the feature map produced by the convolution layer with a filter size or output dimension of half of the previous convolution layer. This also applies to the convolutional layer configuration itself. Maxpooling also functions as a dominant value retrieval where in each 3x3 kernel region used, max pooling takes the maximum value. This means that only the most important or dominant information is passed on to the next layer, while less important information is ignored. This helps the network to focus on the most significant features.

Furthermore, the CAE decoder part proposed in this paper is performed to reconstruct and restore the dimension of the encoded features. The filter size of the convolution layer that is half larger than the previous convolution layer is made until the output layer obtains the same dimensions of the reconstructed image of Babad Lombok as the input image. Between the

Table 1. Configuration table of the CAE architecture used for the reconstruction process that can accept input and output dimensions of 64x64 reconstruction results. [Total params: 12,785 (49.94 KB) Trainable; params: 12,785 (49.94 KB); Non-trainable params: 0 (0.00 B)]

Layer (type)	Output Shape	Param
conv2d_201 (Conv2D)	(None, 64, 64, 32)	320
max_pooling2d_87 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_202 (Conv2D)	(None, 32, 32, 16)	4,624
max_pooling2d_88 (MaxPooling2D)	(None, 16, 16, 16)	0
conv2d_203 (Conv2D)	(None, 16, 16, 8)	1,160
max_pooling2d_89 (MaxPooling2D)	(None, 8, 8, 8)	0
conv2d_204 (Conv2D)	(None, 8, 8, 8)	584
up_sampling2d_86 (UpSampling2D)	(None, 16, 16, 8)	0
conv2d_205 (Conv2D)	(None, 16, 16, 16)	1,168
up_sampling2d_87 (UpSampling2D)	(None, 32, 32, 16)	0



(a) (b) (c)

Figure 6 (a) The original image section of Babad Lombok; (b) The reconstruction result from the trained CAE model; (c) The ground truth of the tested image section of Babad Lombok

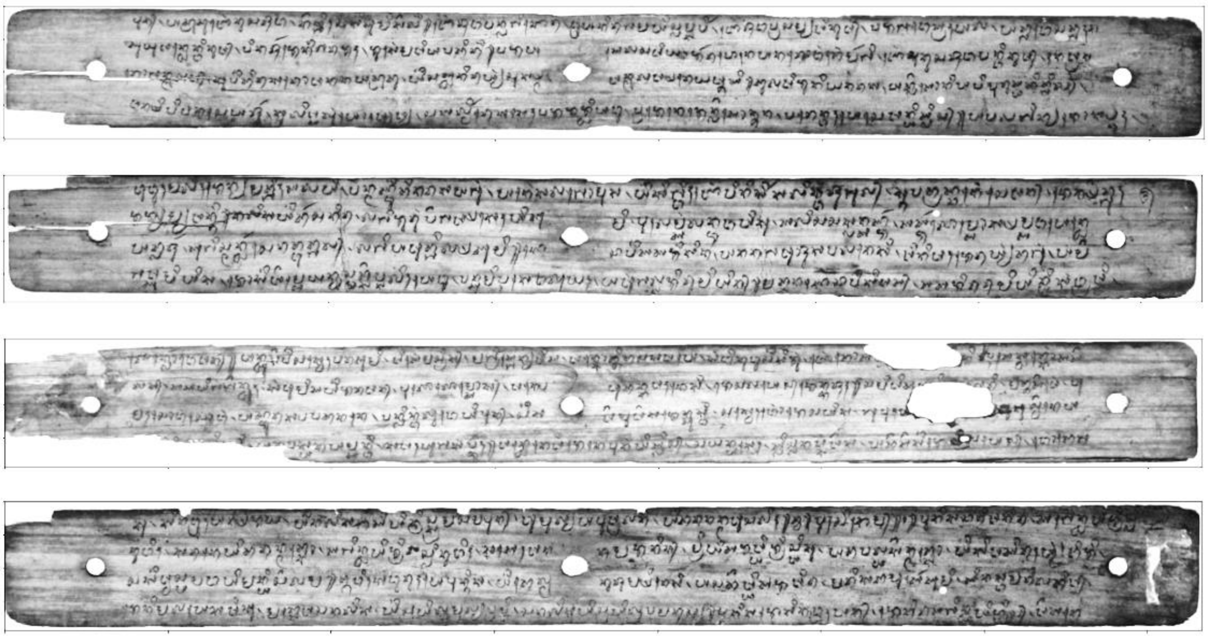


Figure 5 The original image of Babad Lombok that will be reconstructed or repaired with the proposed CAE method

convolution layers created in this decoder section, an upSampling layer is inserted whose purpose is to recover twice the dimensions of the feature map results in the convolution layer. The upSampling layer is also useful for generating image details, allowing the model to create an image that looks similar to the given ground truth image.

The architecture of the CAE model for image repair of Babad Lombok was designed and executed using Python with the Keras Tensorflow library. Table 1 is the result of the execution of the designed model where the input and output layers have the same dimension.

C. Results and Discussion

The CAE architecture designed in this paper is trained to extract script pattern information from the manuscript image of Babad Lombok. The original image of Babad Lombok is given to be able to reconstruct a better image based on the groundtruth data it provides. Configurations such as batch_size = 64, verbose = 1, epochs = 25, validation_split = 0.1, and shuffle = False are given in the model fitting process. Finally, the proposed CAE has achieved training and validation accuracy of 90% and 85% with loss values of 0.0322 and 0.0618, respectively.

In the process, the image of Babad Lombok was first divided into 4 parts to facilitate the creation of the ground truth image for clearer results. However, the training process is still carried out on the entire image which is recombined. Figure 5 is one of the sample image pieces that were tested again with the CAE model after training. Image 5a is a sample input image of Babad

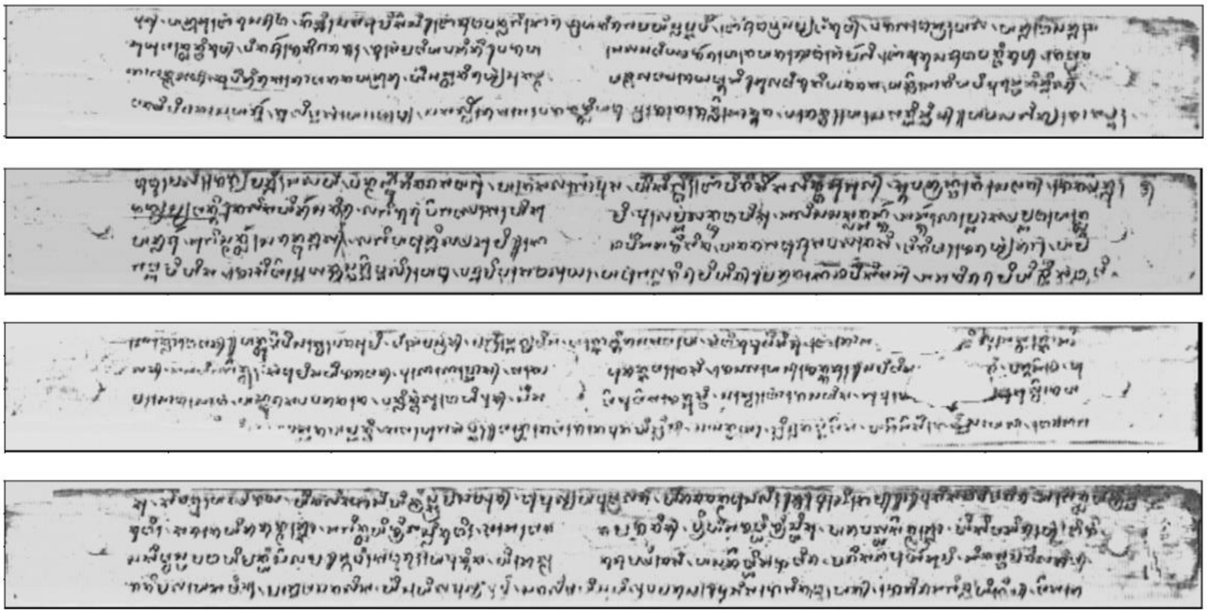


Figure 7 Image of the reconstruction or repair of Babad Lombok with the proposed CAE method

Lombok when reconstructed with the proposed CAE and produces an improved image as shown in Figure 5b. In general, the reconstruction or repair results show that the writing contained in the original image is clarified compared to the background. The reconstructed image in Figure 5b is also close to the similarity with the ground truth image or Figure 5c.

Furthermore, we also tested the proposed CAE model to perform reconstruction or repair on several images as shown in Figure 6. The image of Babad Lombok that was damaged was also included in this testing process. This is certainly outside the topic of the purpose of this research, but we must test it to see the reconstruction results. Figure 7 is the result of the reconstruction or repair process of all parts of the Babad Lombok image. In general, the results shown are in accordance with the objectives of this paper where the writing on the Babad Lombok image can be highlighted so that it is clearer than the background. The writing on the damaged image can also be improved, but to repair the missing writing is the challenge of further research for this Babad Lombok image.

Furthermore, to see the performance of the designed CAE architecture during the training process in this paper, we model it in the form of a graph as shown in Figure 8. The graph displays the performance of the Convolutional Autoencoder (CAE) model during the training process, which is shown through two main metrics: accuracy and loss. The graph on the left depicts the change in accuracy, while the graph on the right shows the change in loss value over several epochs.

In the accuracy graph, the Y-axis shows the accuracy value and the X-axis shows the number of training epochs or iterations. The blue line represents the accuracy on the training data, while the orange line represents the accuracy on the validation data. At the beginning of the training, the accuracy on both the training and validation data starts from around 0.84. As the training progresses, the accuracy on the training data increases gradually, while the accuracy on the validation data rises rapidly and then stabilizes at around 0.94. This shows that the model is getting better at classifying the data with each iteration of training.

The loss graph depicts the loss value during training, with the Y-axis representing the loss value and the X-axis representing the number of epochs. The blue line represents the loss on the training data, while the orange line shows the loss on the validation data. At the beginning of training, the loss values on both training and validation data start at around 0.08. During the first few epochs, the loss value decreases rapidly, and then stabilizes at a lower value. At the end of the training, the loss value on the validation

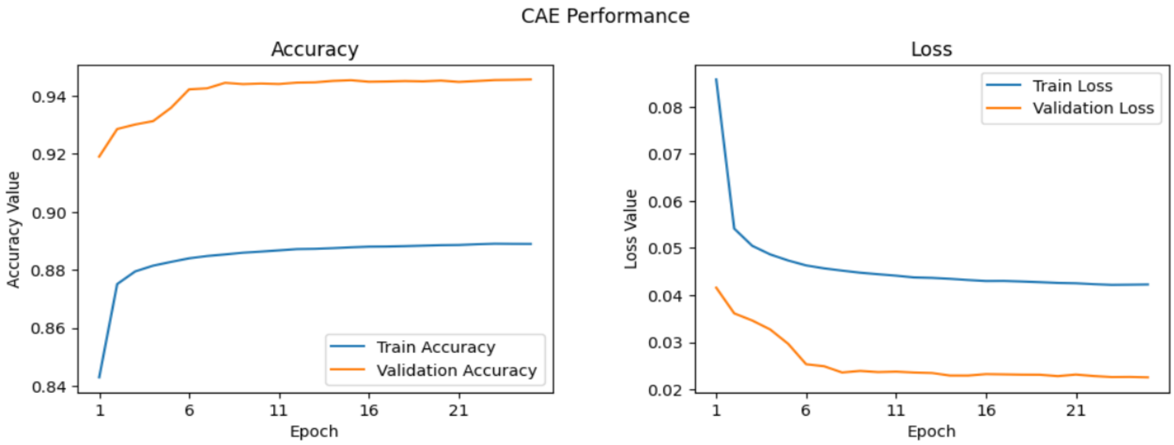


Figure 8 CAE performance graph during training on image reconstruction of Babad Lombok

data stabilizes around 0.02, indicating that the model has successfully minimized the prediction error.

Overall, these two graphs show that the CAE model experienced significant performance improvement during training. The increase in accuracy and decrease in loss values indicate that the model is more effective in predicting new data. The stability of the accuracy and loss values in the validation data also indicates that the model does not experience overfitting, where the model's performance in the training and validation data remains consistently good. This indicates that the trained CAE model has good generalization and is ready to be used on real data.

CONCLUSIONS AND SUGGESTIONS

Research on the image of Babad Lombok has not been done too much to date and is certainly interesting to do. On the other hand, this is a form of preserving the cultural heritage of previous people. This paper proposes the implementation of the use of convolution autoencoder (CAE) in the restoration or improvement of the image of Babad Lombok. The goal is to make the writing contained therein appear clearer than the background. Fully Convolution Autoencoder CAE architecture consists of 3 convolutional layers in the encoder and 5 deconvolutional layers in the decoder. CAE is designed to be able to accept input grayscale image of dimension (64, 64, 1) and reconstruct it with the same dimension. The CAE architecture configuration designed for the reconstruction process can accept the input and output dimensions of 64x64 reconstruction results. In the process, the two types of data are cut to 64x64 size iteratively along the original size of the Babad Lombok image. The process produces input and target data for the CAE training process in this study, each of which is 48,288 images. Testing the trained autoencoder model showed that the babad image was successfully improved so that the quality of the writing contained therein appeared clearer before reconstruction. Finally, the proposed CAE has achieved training and validation accuracy of 89.09% and 94.57% with loss values of 0.0418 and 0.0226, respectively.

The CAE model proposed in this paper has been able to clarify the script content contained in the image of Babad Lombok compared to its background. The result of reconstruction or visual image enhancement shows a significant change from the original image. There are several findings that can be used as a basis for further research. The CAE model in this paper is limited to sharpen the script writing compared to the background so that research on how to reconstruct the damaged part of the script writing needs to be done. Comparison of the accuracy of repair results using multi-layer input reconstruction also needs to be done considering that the input image of Babad Lombok is a color image.

REFERENCES

An, Jinwon, and Sungzoon Cho. 2015. "Variational Autoencoder Based Anomaly

Detection Using Reconstruction Probability." *Special lecture on IE* 2(1): 1–18.

Dixit, Umesh D, and M S Shirdhonkar. 2015. "A Survey on Document Image Analysis and Retrieval System." *International Journal on Cybernetics & Informatics (IJCI)* 4(2): 259–70.

Freeman, William T, Egon C Pasztor, and Owen T Carmichael. 2000. "Learning Low-Level Vision." *International journal of computer vision* 40: 25–47.

Hammouche, Rabah, Abdelouahab Attia, Samir Akhrouf, and Zahid Akhtar. 2022. "Gabor Filter Bank with Deep Autoencoder Based Face Recognition System." *Expert Systems with Applications* 197: 116743.

Hinton, Geoffrey E, Alex Krizhevsky, and Sida D Wang. 2011. "Transforming Auto-Encoders." In *Artificial Neural Networks and Machine Learning--ICANN 2011: 21st International Conference on Artificial Neural Networks, Espoo, Finland, June 14-17, 2011, Proceedings, Part I 21*, , 44–51.

Kaur, Roopdeep, Gour Karmakar, and Muhammad Imran. 2023. "Impact of Traditional and Embedded Image Denoising on CNN-Based Deep Learning." *Applied Sciences*. doi:10.3390/app132011560.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. 2015. "Deep Learning." *nature* 521(7553): 436–44.

Liu, Tong, Jinzhen Wang, Qing Liu, Shakeel Alibhai, Tao Lu, and Xubin He. 2021. "High-Ratio Lossy Compression: Exploring the Autoencoder to Compress Scientific Data." *IEEE Transactions on Big Data* 9(1): 22–36.

Liu, Weibo, Zidong Wang, Xiaohui Liu, Nianyin Zeng, Yurong Liu, and Fuad E Alsaadi. 2017. "A Survey of Deep Neural Network Architectures and Their Applications." *Neurocomputing* 234: 11–26.

Mallik, Anupama, Santanu Chaudhury, Vijay Chandru, and Sharada Srinivasan. 2017. *Digital Hampi: Preserving Indian Cultural Heritage*. Springer.

Mao, Xiao-Jiao, Chunhua Shen, and Yu-Bin Yang. 2016. "Image Restoration Using Convolutional Auto-Encoders with Symmetric Skip Connections." *arXiv preprint arXiv:1606.08921*.

Mintosih, Sri, Amurwani Dwi Lestarining, and others. 1999. *Pengkajian Nilai Budaya Naskah Babad Lombok Jilid 1*. Direktorat Jenderal Kebudayaan.

Muhammad Tajuddin Anwar, Syahroni Hidayat, Ahmat Adil. 2021. "Transformasi Lontar Babad Lombok Menuju Digitalisasi Berbasis Natural Gradient Flexible (NGF)." *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)* 8(2).

Otsu, Nobuyuki, and others. 1975. "A Threshold Selection Method from Gray-Level Histograms." *Automatica* 11(285–296): 23–27.

Parida, Priyadarsan, and Nilamani Bhoi. 2018. "Feature Based Transition Region Extraction for Image Segmentation: Application to Worm Separation from Leaves." *Future Computing and Informatics Journal* 3(2): 262–74. doi:10.1016/J.FCIJ.2018.08.001.

Raha, Poulami, and Bhabatosh Chanda. "Restoration of Historical Document Images Using Convolutional Neural Networks." 7: 3–8.

Rama Lakshmi, Gali, G Divya, D Bhavya, Ch Sai Jahnavi, and B Akila. 2023. "A Review on Image Denoising Algorithms for Various Applications." In *Proceedings of Fourth International Conference on Communication, Computing and Electronics Systems: ICCCES 2022*, , 839–47.

Sehgal, Rashmita, and Vandana Dixit Kaushik. 2022. "CT Image Denoising Using Bilateral Filter and Method Noise Thresholding in Shearlet Domain." In *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2022, Volume 1*, Springer, 99–106.

Sreedevi, Indu, Rishi Pandey, N Jayanthi, Geetanjali Bhola, and Santanu Chaudhury. 2013. "Ngfica Based Digitization of Historic Inscription Images." *International Scholarly Research Notices* 2013.

Tajuddin, Muhammad. "Penelitian Naskah Kuno Babad Lombok." https://tajuddin.web.id/detail-naskah/9.

Tajuddin, Muhammad, Ahmat Adil, Syahroni Hidayat, Zaenal Abidin, and R Fanny Priniti. 2019. "Naskah Lontar Sasak Di Era Industri 4.0 Berbasis Cots Method." In *Prosiding Seminar Sains Nasional Dan Teknologi*,.

Tensmeyer, Chris, and Tony Martinez. 2020.

"Historical Document Image Binarization: A Review." *SN Computer Science* 1(3): 173.

Wang, Mei, and Weihong Deng. 2021. "Deep Face Recognition: A Survey." *Neurocomputing* 429: 215–44. doi:10.1016/j.neucom.2020.10.081.

Yasenko, Lev, Yaroslav Klyatchenko, and Oksana Tarasenko-Klyatchenko. 2020. "Image Noise Reduction by Denoising Autoencoder." In *2020 IEEE 11th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, , 351–55.

You, Ning, Libo Han, Daming Zhu, and Weiwei Song. 2023. "Research on Image Denoising in Edge Detection Based on Wavelet Transform." *Applied Sciences* 13(3): 1837.