

OPTIMIZING HADITH CLASSIFICATION USING NEURAL NETWORKS: A STUDY ON BUKHARI AND MUSLIM TEXTS

Rasenda¹, Luky Fabrianto², Novianti Madhona Faizah³

Universitas Teknologi Muhammadiyah Jakarta¹

Universitas Nusa Mandiri²

Universitas Tama Jagakarsa³

*Email: 1rasenda@utmj.ac.id, 2luky.lfb@nusamandiri.ac.id, 3novianti@jagakarsa.ac.id

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Abstract

The Bukhari and Muslim hadith collections encompass a total of 7008 hadith sentences, but it is not immediately clear which of these hadiths fall into the categories of prohibitions or orders. To enhance understanding and accessibility for readers, this study focuses on classifying these hadiths through a systematic process. The classification involves several key stages: Text Pre-processing, pre-processing the raw text data to clean and normalize (Stemming, Stopword Removal and Tokenization), Word vector features are extracted to capture the semantic relationships and contextual meanings of the words, then processed into a neural network model based on a multilayer perceptron (MLP) architecture (Model Architecture, Training and Optimization). The approach leverages the strength of neural networks, particularly through the use of multiple layers and feature extraction via word vectors, which significantly contributes to the accuracy of the classification process. The results of the study is very good, with a high accuracy rate of 97.72% achieved by employing a model with two layers and 256 neurons

Keywords: *Classification, Hadith, Multilayer Perceptron, Neural Network, Word Vector.*

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*Corresponding Author: Rasenda

1. INTRODUCTION

Text classification research on Hadith data is still relatively rare, even though Hadith data is now easily accessible through the internet or various applications. Processing Hadith data is crucial as it contains behavioral guidelines for Muslims in accordance with the Sunnah of Prophet Muhammad Shallallahu 'Alaihi Wasallam [1]. In the context of Hadith text processing, a command is referred to as "amar," and a prohibition is referred to as "nahi." According to the majority of usul al-fiqh scholars, "amar" is a command issued by a higher authority to a lower one, while "nahi" is a prohibition issued by a higher authority to a lower one [2][3].

Natural Language Processing (NLP) using WordVector has proven to be effective in encoding word relationships in vector space, which is beneficial for various NLP tasks [4][5]. One commonly used method in NLP is Neural Network, which mimics the workings of the human neural network for pattern recognition and classification [6]. In designing a Neural Network, it is crucial to determine the learning

method, which involves updating synaptic weights based on input signals and the expected output. Neural Networks typically consist of several neurons as information processing units [7][8]. The classification model evaluation uses a confusion matrix that shows the actual number of cases from the observed class to be predicted [9].

Several studies related to text mining on Hadith show various methods and accuracy results. The study by [10], titled "Application of Particle Swarm Optimization on Feedforward Neural Network for Classification of Bukhari Hadith Text in Indonesian Translation," used BP-FNN and PSO-FNN methods on a Hadith classification dataset, achieving BP-FNN accuracy of 88.57% and PSO-FNN of 89.5%. [11] The results revealed that Machine Learning performs better than DL using the Matan input data, with a 77% F1-score. Deep Learning performed better than ML using the Sanad input data, with a 92% F1-score. [12] In their study "Classification of Suggestions, Prohibitions, and Information in Sahih Al-Bukhari Hadiths Based on Unigram Model Using Artificial Neural Network (ANN)" used n-gram and ANN

models, yielding an f1-score of 85% for the categories of suggestions, prohibitions, and information. [13] In "Classification of Hadith Authenticity Based on Hadith Narrators Using Principal Component Analysis (PCA) and Backpropagation Neural Network (BPNN)," PCA and BPNN were used on the categories *sahih*, *hasan*, and *dhaif*, with an accuracy of 86.53%. The study [14] presents a novel taxonomy/classification of hadith detection techniques. Our taxonomy is unique compared to others because all hadith components are categorized based on four layers which include authority, narrators, and the *Matan* and *Isnad* status. The study [15] titled "Multi-Label Topic Classification of Hadith of Bukhari (Indonesian Language Translation) using Information Gain and Backpropagation Neural Network" used BPNN on the categories of suggestions, prohibitions, and commands, with an accuracy of 88.42%. Meanwhile, [16] in "Classification of Hadith into Positive Suggestion, Negative Suggestion, and Information" used TF-IDF, Baseline, SVM, and ANN on the categories of commands, prohibitions, and information, achieving a Baseline f1-score of 69% and ANN 79%. These studies illustrate the use of various techniques in the classification of Hadith texts with varying results.

Based on previous research, neural network algorithms have proven effective in classifying Hadith texts. Neural networks are considered superior due to their non-linear nature, making them suitable for high-complexity problems, and their adaptability, allowing them to effectively map inputs to outputs. Additionally, neural networks are fault-tolerant, continuing to function even with some degree of error, and capable of generalization, processing new data based on learned experience [6][17]. Therefore, this study will use neural networks to classify Hadiths narrated by Bukhari and Muslim into categories of prohibitions or commands.

2. RESEARCH METHOD

The research stages, as shown in Figure 1 below.

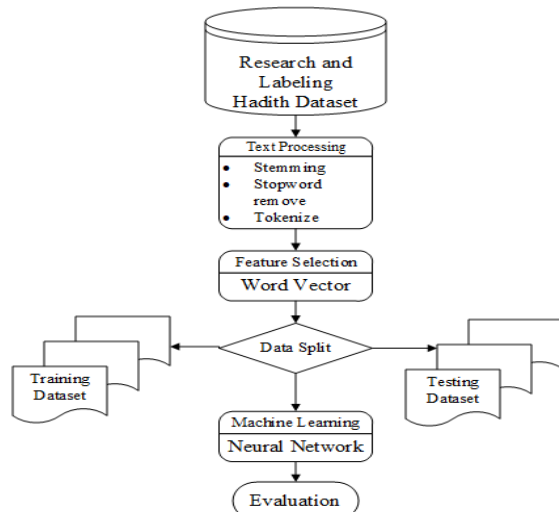


Figure 1. Research stages

This research utilizes a dataset of Hadith from *Shahih Bukhari* and *Muslim*, consisting of 7008 *matan*, labeled according to the classification of either prohibition or command. During the pre-processing stage, the *StemmerFactory* library from the *Sastrawi* module in Python 3.7 was used. The pre-processing process involves three stages: stemming, stopword removal, and tokenization. Stemming was performed using the *StemmerFactory* method from the *Sastrawi* library, executed on sentences with the *create stemmer* function. Stopwords were removed using *StopWordRemoverFactory* from the *Sastrawi* library, executed with *create stop word remover*. Tokenization was done using *word_tokenize* from the *NLTK* library.

The feature used is the word vector from the *Gensim* library in Python 3.7, which was employed to calculate vocabulary and similarity values from the Hadith dataset [18]. Word vectors were then used for one-hot encoding to convert text into binary values to be input into the neural network. Data was split into training and testing sets using the *scikit-learn* library. The neural network model was built using the *Keras* library in Python 3.7 by adding layers with the *dense* function. Input was determined based on the similarity size in the word vector, with the *relu* activation function used for the input and hidden layers, and the *Sigmoid* activation function for the output layer [19]. The *Adam* optimizer was employed with binary cross entropy as the loss function, and the epoch and batch size values were set accordingly [20]. Figure 2 illustrates the architecture for building the neural network.

Input layer (Dense)	→	Aktivasi Relu
Size Input	→	Size Similarity in Word Vector
Hidden layer (Dense)	→	Aktivasi Relu
Output layer (Dense)	→	Aktivasi Sigmoid
Optimizer	→	Adam
Loss	→	Binary Crossentropy
Epoch	→	Value Epoch
Batch Size	→	Value Batch Size

Figure 2. Developing Neural Network

The final stage of this research involves evaluating the experiment using a Confusion Matrix, as shown in Table 1. The accuracy can then be calculated using the formula provided below [21]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \% \tag{1}$$

Table 1. Confusion Matrix

	Actual Positive Class	Actual Negative Class
Predictive Positive Class	True Positive (TP)	False Negative (FN)
Predictive Negative Class	False Positive (FP)	True Negative (TN)

Legend: TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

3. RESULT AND DISCUSSION

An example of the pre-processing process involves a Hadith that reads, "All actions are judged by intentions, and each person will be rewarded according to what they intended. Whoever migrates for worldly gain or to marry a woman, his migration is for that which he intended." After undergoing stemming using the Sastrawi library, stopword removal, and tokenization with the NLTK library, the Hadith is transformed as shown in Figure 3 below.

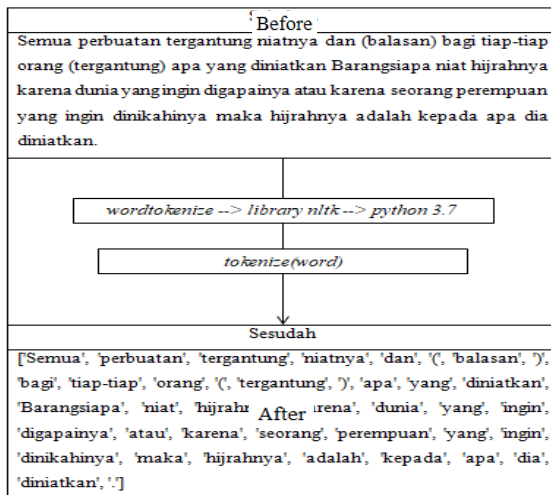


Figure 3. Before and After Tokenize result

The Wordvector used in this research was configured with a min_count of 5, resulting in a vocabulary of 3,393 words. Figure 4 shows a visualization of the vocabulary after setting min_count to 1000, which reduces the vocabulary to 65 words..

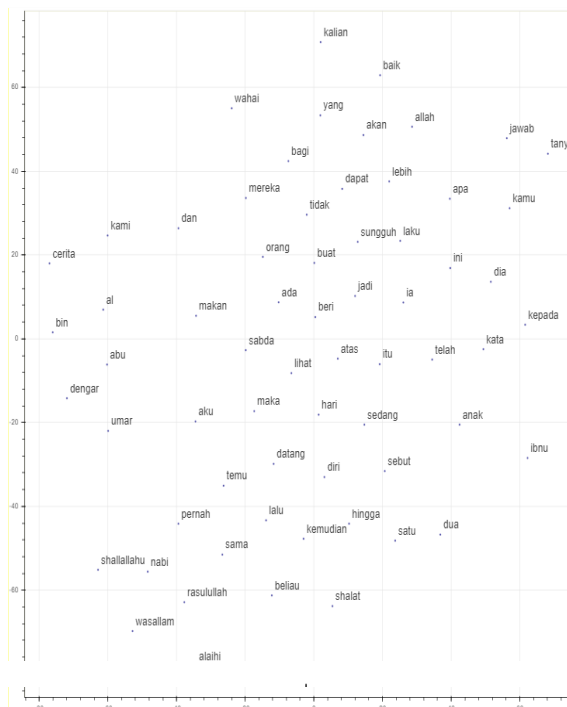


Figure 4. Visualization of Vocabulary Results

The Wordvector used to find similarity in this research was configured with windows = 5 and size = 200. Table 2 provides an example of the similarity results for the word "hari" (day). Figure 5 illustrates the visualization of the similarity for the word "hari."

Table 2. Similarity word 'Hari' result

-0.998	-0.1546	-1.606	-1.92564	0.171547
0.276	1.00972	-0.75	-0.66444	1.068439
0.418	-0.0405	-0.709	0.424856	1.530188
.....
0.879	-0.1263	-0.939	-0.77086	-1.67769
2.71	0.79881	1.6754	0.608546	0.101442
-0.178	-1.2313	0.1619	1.066376	-0.04765

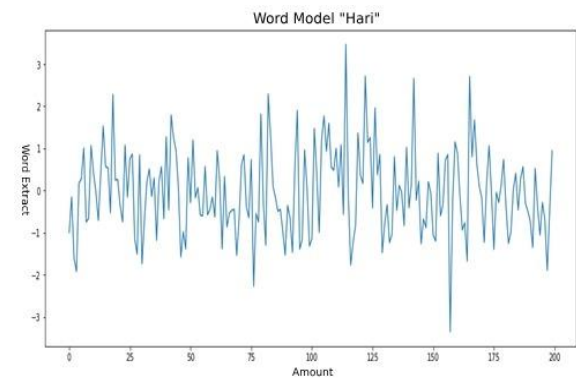


Figure 5. Visualisasi Similarity 'Hari' result

The top 5 most similar words to "hari" are shown in Table 3, and their visualization is presented in Figure 6.

Table 3. Most similarity Top 5 word 'hari' result

Word	Most_Similarity
pagi	0.453531414
bulan	0.453418076
siang	0.450212121
raya	0.431948364
malam	0.430161893



Figure 6. Visualization of similarity 'hari' result

Next is an example of the top 5 most similar words to "hari" + "islam" - "kiamat," as shown in Table 4. The visualization of these top 5 most similar words is presented in Figure 7.

Table 4. Most_similarity words "hari" + "islam" - "kiamat" result

Kata	Most_Similarity
masa	0.379982561
talak	0.372045457
baiat	0.36673528
ujung	0.362578362
pulang	0.34503299

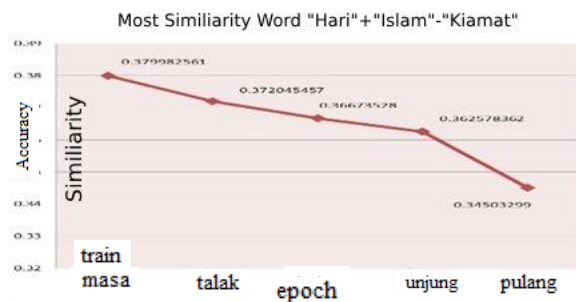


Figure 7. Visualization 'hari' + 'islam' - 'kiamat' result

Data was divided using cross-validation, consisting of 90% training data (6307 samples) and 10% testing data (701 samples) from a total of 7008 samples. The neural network type used is a multilayer perceptron, which is effective for classification by constructing several simple yet effective layers. The model employed is a sequential model with dense layers for adding layers. The input size is 200, derived from feature selection, with ReLU as the activation function for the first and intermediate layers, and Sigmoid for the output layer. The optimizer used is Adam, with binary cross entropy as the loss function, 25 epochs, and a batch size of 1024. The parameters adjusted include the number of layers and neurons in the hidden layers to achieve the best accuracy. Table 5 summarizes the accuracy results from three different neural network experiments..

Table 5. Experiment result recapitulations

Experiments	Layer	Neurons	Accuracy
A	2	128	0.9757
	5	128	0.9714
	10	128	0.9643
B	2	256	0.9772
	5	256	0.9686
	10	256	0.9728
C	2	512	0.9757
	5	512	0.9757
	10	512	0.9715

The confusion matrix results from Experiment B are shown in Table 6 below.

Tabel 6. Confusion Matrix result

	Actual 0	Actual 1
Pred. 0	22 (TN)	13 (FP)
Pred. 1	3 (FN)	663 (TP)

From the confusion matrix results, the accuracy calculated is 97.72%. Figure 8 illustrates the visualization of the accuracy history from this research.

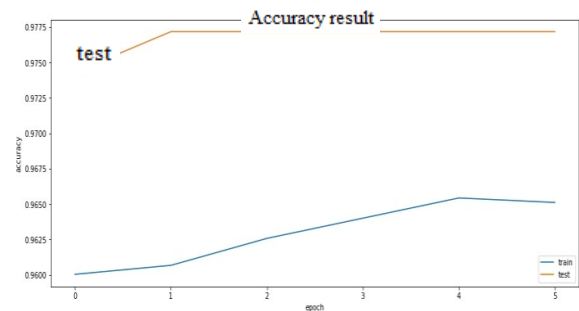


Figure 8. Accuracy History result

The accuracy results show that the training accuracy is lower than the testing accuracy, indicating that the model is not overfitting and performs well on the test data.

4. CONCLUSION

The conclusion of this research indicates that effective text pre-processing yields optimal results in word analysis within sentences. The use of word vectors as feature selection aids the neural network in extracting the meaning of sentences. Neural networks are effective for classifying Hadith into categories of prohibition or command. Experiment B's architecture, which employs two layers and 256 neurons in the hidden layer, achieved the highest accuracy of 97.72%.

5. REFERENCE

- [1] D. Sholehat and D. A. Alfiani, "Pengaruh Pola Asuh Permisif dari Orang Tua Terhadap Prestasi Belajar Siswa Pada Mata Pelajaran Al-Qur'an Hadits Kelas IV di Madrasah Ibtidaiyah," *Indones. J. Elem. Educ.*, vol. 1, no. 1, pp. 1–12, 2019.
- [2] A. Mufid, "Jamal Al-Banna's Perspective on The Understanding Reconstruction of Changing Munkar: Decolonization of the Study of Islamic Thought From Textual to Contextual Knowledge," *J. Islam. Stud. Humanit.*, vol. 7, no. 1, pp. 84–95, 2022, doi: 10.18326/mlt.v7i1.7041.
- [3] H. M. Abdelaal, B. R. Elemery, and H. A. Youness, "Classification of Hadith According to Its Content Based on Supervised Learning

- Algorithms,” *IEEE Access*, vol. 7, pp. 152379–152387, 2019, doi: 10.1109/ACCESS.2019.2948159.
- [4] E. M. Dharma, F. Lumban Gaol, H. Leslie, H. S. Warnars, and B. Soewito, “THE ACCURACY COMPARISON AMONG WORD2VEC, GLOVE, AND FASTTEXT TOWARDS CONVOLUTION NEURAL NETWORK (CNN) TEXT CLASSIFICATION,” *J. Theor. Appl. Inf. Technol.*, vol. 31, no. 2, 2022, Accessed: Aug. 30, 2024. [Online]. Available: www.jatit.org.
- [5] S. Park, J. Byun, S. Baek, Y. Cho, and A. Oh, “Subword-level word vector representations for Korean,” *ACL 2018 - 56th Annu. Meet. Assoc. Comput. Linguist. Proc. Conf. (Long Pap.)*, vol. 1, pp. 2429–2438, 2018, doi: 10.18653/v1/p18-1226.
- [6] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, “A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects,” *IEEE Trans. Neural Networks Learn. Syst.*, vol. 33, no. 12, pp. 6999–7019, Dec. 2022, doi: 10.1109/TNNLS.2021.3084827.
- [7] T. Kim *et al.*, “Spiking Neural Network (SNN) With Memristor Synapses Having Non-linear Weight Update,” *Front. Comput. Neurosci.*, vol. 15, p. 646125, Mar. 2021, doi: 10.3389/FNCOM.2021.646125/BIBTEX.
- [8] M. W. Habibi, “Permainan edukatif puzzle surat Al-Qur’an (Q-Puzzle) menggunakan backpropagation sebagai penentu level permainan,” Jun. 2018.
- [9] I. Dwita, S. Tarigan, R. Habibi, R. Nuraini, and S. Fatonah, “Evaluasi Algoritma Klasifikasi Machine Learning Kategori Nilai Akhir Tunjangan Kinerja Pegawai,” *J. Sist. Cerdas*, vol. 6, no. 3, pp. 251–261, Dec. 2023, doi: 10.37396/JSC.V6I3.246.
- [10] M. Ghufuran, A. Adiwijaya, and S. Al-Faraby, “Penerapan Particle Swarm Optimization Pada Feedforward Neural Network Untuk Klasifikasi Teks Hadis Bukhari Terjemahan Bahasa Indonesia,” *J. Media Inform. Budidarma*, vol. 2, no. 4, p. 165, 2018, doi: 10.30865/mib.v2i4.951.
- [11] A. Ramzy *et al.*, “Hadiths Classification Using a Novel Author-Based Hadith Classification Dataset (ABCD),” *Big Data Cogn. Comput.* 2023, Vol. 7, Page 141, vol. 7, no. 3, p. 141, Aug. 2023, doi: 10.3390/BDCC7030141.
- [12] A. Y. Prathama *et al.*, “Klasifikasi Anjuran , Larangan dan Informasi pada Hadis Sahih Al-Bukhari berdasarkan Model Unigram menggunakan Artificial Neural Network (ANN),” *J. Teknosains*, vol. 2, no. 3, pp. 1130–1139, 2018, [Online]. Available: <http://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/2573%0Ahttp://eprints.undip.ac.id/35760/>.
- [13] U. Nuha and N. Rochmawati, “Klasifikasi Kesahihan Hadits Berdasarkan Perawi Hadits Menggunakan Principal Component Analysis (PCA) dan Backpropagation Neural Network (BPNN),” *J. Informatics Comput. Sci.*, vol. 1, no. 03, pp. 138–143, Jan. 2020, doi: 10.26740/JINACS.V1N03.P138-143.
- [14] A. A. Fadele, A. Kamsin, K. Ahmad, and H. Hamid, “A novel classification to categorise original hadith detection techniques,” *Int. J. Inf. Technol.*, vol. 14, no. 5, pp. 2361–2375, Aug. 2022, doi: 10.1007/S41870-021-00649-3/FIGURES/4.
- [15] M. Y. Abu Bakar, Adiwijaya, and S. Al Faraby, “Multi-Label Topic Classification of Hadith of Bukhari (Indonesian Language Translation) Using Information Gain and Backpropagation Neural Network,” *Proc. 2018 Int. Conf. Asian Lang. Process. IALP 2018*, pp. 344–350, Jul. 2018, doi: 10.1109/IALP.2018.8629263.
- [16] S. Al Faraby, E. R. R. Jasin, A. Kusumaningrum, and Adiwijaya, “Classification of hadith into positive suggestion, negative suggestion, and information,” *J. Phys. Conf. Ser.*, vol. 971, no. 1, p. 012046, Mar. 2018, doi: 10.1088/1742-6596/971/1/012046.
- [17] T. S. Gunawan *et al.*, “Development of video-based emotion recognition using deep learning with Google Colab,” *TELKOMNIKA (Telecommunication Comput. Electron. Control.)*, vol. 18, no. 5, pp. 2463–2471, Oct. 2020, doi: 10.12928/TELKOMNIKA.V18I5.16717.
- [18] A. Khandare, N. Agarwal, A. Bodhankar, A. Kulkarni, and I. Mane, “Study of Python libraries for NLP,” *Int. J. Data Anal. Tech. Strateg.*, vol. 15, no. 1–2, pp. 116–128, 2023, doi: 10.1504/IJDATS.2023.132564.
- [19] B. T. Chicho and A. B. Sallow, “A Comprehensive Survey of Deep Learning Models Based on Keras Framework,” *J. Soft Comput. Data Min.*, vol. 2, no. 2, pp. 49–62, Oct. 2021, doi: 10.30880/jscdm.2021.02.02.005.
- [20] K. K. Chandriah and R. V. Naraganahalli, “RNN / LSTM with modified Adam optimizer in deep learning approach for automobile spare parts demand forecasting,” *Multimed. Tools Appl.*, vol. 80, no. 17, pp. 26145–26159, Jul. 2021, doi: 10.1007/S11042-021-10913-0/FIGURES/5.
- [21] J. Xu, Y. Zhang, and D. Miao, “Three-way confusion matrix for classification: A measure driven view,” *Inf. Sci. (Ny.)*, vol. 507, pp. 772–794, Jan. 2020, doi: 10.1016/J.INS.2019.06.064.