

Supporting Application Fast Learning of Kitab Kuning for Santri' Ula Using Natural Language Processing Methods

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Abstract

Education in Islamic boarding schools is one of Indonesia's traditional forms of education that teaches Islamic religious teachings, including studying the yellow classic books as the primary source of spiritual learning. However, learning the Yellow classic book is often complicated by 'ula students (early level students) because Arabic is without harakat or lines, and the material studied is very complex. To overcome these challenges, this research aims to develop a yellow Islamic classic book learning support application for 'ula students using the Natural Language Processing (NLP) method. This application has an interactive chatbot feature that helps students understand the contents of the yellow book more effectively and enjoyably. The research method includes literature study, data collection, data processing, and system development using the Sparse Categorical Cross Entropy algorithm in Natural Language Processing to improve the accuracy of chatbot responses. This application provides an innovative solution by presenting an interactive learning experience that can be accessed anytime and anywhere, thus facilitating Santri learning outside the boarding school environment. The results show that learning for 'ula students with the Natural Language Processing method is very good and easy to understand. The test shows that the accuracy of the application reaches 100% with a low error value (loss), which is 0%. It can be recognized that the effectiveness of Natural Language Processing in supporting yellow book learning, maintaining the tradition of Islamic education in the digital era, and helping teachers and parents monitor the development of students.

Keywords: Learning Application, Kitab Kuning, Santri' Ula, Natural Language Processing, Chatbot.

1. Introduction

Education in boarding schools is a traditional education form that is still widely found in Indonesia. Islamic boarding schools teach students about the teachings of Islam, including studying the Yellow Book as one of the primary sources of religious learning. The Yellow Islamic classic book is a religious literature in Arabic that contains necessary materials in Islamic teachings. However, the learning process of the yellow Islamic classic book is often considered difficult by Santri 'ula (early-level students) due to the language used and the complexity of the material.

Santri' ula often faces significant challenges when studying yellow classical books. Arabic without harakat requires an in-depth understanding of the grammar (nahwu and Sharaf), which is usually not mastered by novice santri. The complexity of the kitab kuning material also makes it difficult for Santri to understand the book's contents independently. In addition, limited time and access to teachers, especially outside formal learning hours, further exacerbate the gap in understanding [1].

This challenge is exacerbated by the lack of interactive learning media that supports learning needs in the digital era. Traditional teaching methods that rely solely on the physical presence of students and teachers are often insufficient to address evolving learning needs. This causes yellow book learning to be slow, inefficient, and less flexible, thus hindering Santri in achieving optimal understanding [2].

This condition creates an urgency to develop technology-based solutions to help 'ula santri overcome difficulties in learning the yellow classical books. Natural Language Processing (NLP) methods offer an excellent opportunity to create more personalized and affordable learning. With algorithms such as Sparse Categorical Cross-Entropy Loss, NLP-based applications can provide interactive learning experiences, help understand the contents of the yellow classical books independently, and accelerate the learning process. This innovation not only addresses the educational needs of Santri but also plays a vital role in preserving the tradition of Islamic learning in the modern era.



Natural Language Processing (NLP) is a branch of computer science that focuses on the interaction between computers and languages that are commonly used in everyday life. NLP seeks to develop techniques to enable computers to understand natural human language. Every natural language spoken by humans in different countries has differences in writing and pronunciation [3]. Overall, this research aims to develop a web-based system with NLP methods to help 'ula students. With this system, it is expected to learn effectively and interactively.

2. Literature Review

2.1. Santri' Ula

Santri 'Ula is a level of education in a pesantren hut equivalent to elementary school (SD) or Madrasah Ibtidaiyah (MI). Santri 'Ula comes from the word "Ula", which means the beginning or the beginning and is the first level in the education system at the boarding school. 'Ula level boarding schools are required to accept citizens aged between 7 (seven) and 12 (twelve) years old as santri, according to their capacity. The admission process does not require the ability to read, write, or count. Santri 'Ula at this level is important as a strong foundation for students to continue to higher levels in the pesantren. The Santri 'ula level education also aims to form a good Santri character. Through religious lessons and other religious activities, santri are taught to have good morals, perform worship properly, and uphold religious values [4].

2.2. Kitab Kuning

Kitab kuning generally refers to classical books, not contemporary books, which are usually studied in pesantren, especially salaf pesantren. Etymologically, the word "Kitab" comes from Arabic, meaning book, while "yellow" refers to the distinctive colour of the book. The yellow book has its roots in the manuscripts of scholars after the Khulafaa al-Rashidin period, which were written in Arabic without harakat marks. The Qur'an was primarily written as a guide for non-Arabs and to create uniformity in its recitation. Meanwhile, for those who mastered Arabic grammar, reading the text without harakat was not a difficulty because of their understanding of the structure of the language. The yellow book is also known as kitab gundul because it is not equipped with harakat such as fathah, kasrah, dhammah, or sukun. Therefore, reading the Yellow Book requires expertise in Arabic grammar, especially in nahwu and Sharaf [5].

2.3. History of Natural Language Processing

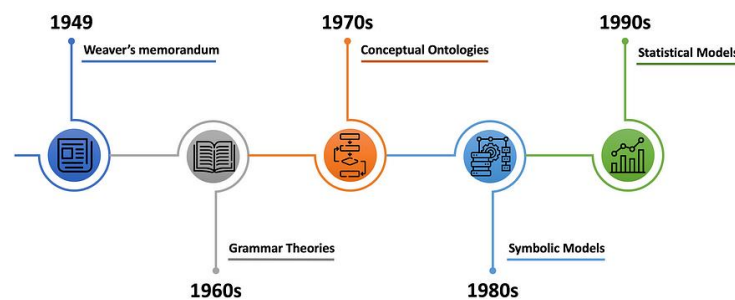


Fig 1. History of NLP from 1949-1980

Weaver's memorandum (Shannon and Weaver, 1949) introduced machine translation (MT), inspiring projects like the Georgetown experiment (1955), which translated Russian sentences into English using hand-coded rules but struggled to scale. Early MT relied on simple dictionary lookups and word reordering, yielding poor results due to lexical ambiguity. Generative grammar (Chomsky, 1957) introduced syntactic structure, but by 1966, the ALPAC report concluded MT was unfeasible, halting much NLP research. Despite setbacks, the late 1960s and 1970s saw advances in semantic representation and prototypes like ELIZA, SHRDLU, and PARRY. Symbolic approaches dominated the 1980s, but statistical models in the 1990s revolutionized NLP with probabilistic machine learning, replacing hand-coded rules [6].

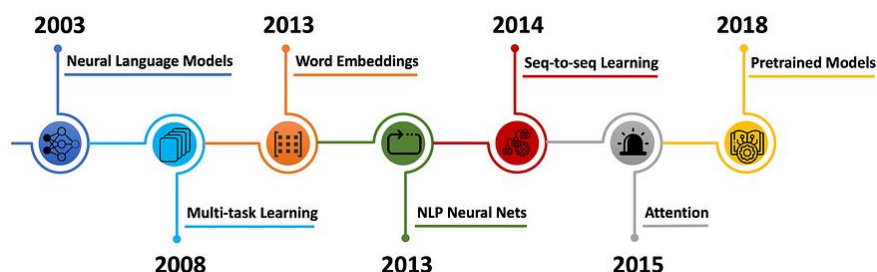


Fig 2. History of NLP from 2003-2015

In the 2000s, neural networks were applied to language modelling, introducing the first neural language model and word embeddings. Later, RNNs, LSTMs, and CNNs became popular for their ability to model sequential and hierarchical data. The Word2Vec model revolutionized word embeddings by enabling large-scale training and improving downstream NLP tasks. In 2014, sequence-to-sequence learning (Sutskever et al.) transformed machine translation, and the attention mechanism addressed key bottlenecks in neural machine translation. The Transformer introduced self-attention, laying the groundwork for large pre-trained language models like BERT and GPT, which have since dominated NLP by enabling efficient learning from vast unannotated corpora, even for low-resource languages [7].

Long Short-Term Memory (LSTM) is a more powerful RNN unit for natural language processing tasks. Recurrent artificial neural networks that are created using LSTM cells are known as LSTM networks. LSTMs were invented by Sepp Hochreiter and Jürgen Schmidhuber in 1997. They are currently the preferred unit in RNNs because they have the concept of memory and can encode powerful data representations. The strength of LSTMs comes from the fact that they maintain a cell state that can remain unchanged across various time steps depending on the gate calculation. This can be seen as a short-term memory the network can hold for extended periods (8).

2.3. Python

Python is a computer programming language often used to build websites and software applications, automate tasks, and analyze data. This programming language is general-purpose, meaning it can be used to create many different programs, not just for specific problems. Due to its flexibility and ease of use, Python has become one of the most popular programming languages. "Python" is derived from "Monty Python," a British comedy troupe. When Guido van Rossum created Python, he was reading a script for the BBC's Monty Python's Flying Circus. He chose the name because it sounded short, unique, and mysterious [9].

Python is a versatile programming language that has recently gained significant popularity, particularly in Natural Language Processing (NLP). With extensive libraries and tools specifically designed for text analysis, Python has become the go-to language for researchers, developers, and data scientists working with textual data. In this article, we will explore the power of Python for NLP and how it can be used as a tool for practical text analysis [10].

2.4. Confusion Matrix

There are several methods to assess the performance of the resulting model, one of which is by using a confusion matrix. A confusion matrix is a table that shows the amount of test data classified correctly and the amount of test data classified incorrectly [11]. One of the parameters used to assess the performance of the classification model is accuracy. Accuracy is the most basic and frequently used performance measure in model evaluation. Accuracy is the ratio of correct predictions compared to the total number of samples. In the confusion matrix, there are several values.

Description:

1. TP = *True Positive* (Objects correctly classified as a positive class).
2. TN = *True Negative* (Objects correctly classified as a hostile class).
3. FN = *False Negative* (Objects that should have been classified as a hostile class but were incorrectly classified as a positive class).
4. FP = *False Positive* (Objects that should have been classified as a positive class but were incorrectly classified as hostile).

These values can be used to calculate accuracy using the following formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \dots\dots\dots (1)$$

Precision measures how accurate a model is in predicting positive outcomes across a range of prediction activities. Precision calculations are commonly used to develop rain prediction models in specific regions. The equation below can be used to determine the amount of precision of an event prediction.

$$\text{Precision} = \frac{TP}{TP+FP} \dots\dots\dots (2)$$

In addition to precision and accuracy, we can also analyze the performance of a system in more depth, such as recall or the system's sensitivity to certain classes. One way to measure recall is by using the following equation.

$$\text{Recall} = \frac{TP}{TP+FN} \dots\dots\dots (3)$$

F1-Score is the average of recall and precision. The optimal F1-Score is 1.0, while the worst score is 0. In general, if the F1-Score scores high, the classification model has good precision and recall. This is expressed mathematically as the following equation.

$$F1 - \text{Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \dots\dots\dots (4)$$

2.5. JSON

JSON stands for JavaScript Object Notation and is a file format used to exchange or share various data across different systems or applications (e.g. from server to client). Data can be transmitted using multiple file formats, such as XML or CSV, but we will discuss JSON today. JSON is very human-readable and easy to understand, making it one of the most popular file formats. JSON is structured data based on JavaScript syntax, making it easier to convert JSON to JavaScript objects. You can also use JSON in other programming languages like Python or Java [12].

3. Research Methods

3.1. Natural Language Processing

Natural Language Processing (NLP) is a set of theoretically motivated computational techniques for analyzing and representing naturally occurring text at one or more levels of linguistic analysis of human-like language for various tasks and applications [13]. Natural language processing (NLP) is a branch of computer science that utilizes computational techniques to learn, understand, and generate human language. NLP enables natural interaction between users and computers [14]. The process of understanding natural language involves syntactic and semantic analysis. The syntactic analysis involves organizing words in sentences to conform to grammatical rules. This process also transforms the arrangement of words into a structure that describes the relationship between words. Meanwhile, semantic analysis focuses on the meaning of each word and sentence. It captures the true sense by processing the logical structure of the sentence, recognizing similarities between words, and understanding the topic discussed in the sentence.

Data preprocessing in NLP is an essential step in developing neural network models, as it ensures that the data is clean, structured, and suitable for training [15]. The following are typical steps in data preprocessing for NLP: tokenization, which is breaking down text into words, phrases, or sentences (tokens). Lemmatization, however, involves reducing words to their basic or dictionary form, known as lemmas. Stemming consists of cutting off a word's prefix or suffix to get its root or base form, known as stem [16].

NLP here will use loss function modelling. Loss Function is an algorithm that measures/calculates how wrong an NN model is. Loss is the measure of this function, which expects loss = 0 because loss is the error produced by the model [17]. One example of a loss function is Sparse Categorical Cross Entropy.

Sparse Categorical Cross Entropy is a loss function commonly used in classification problems. It measures the difference between the predicted probability distribution and the actual probability distribution.

$$Loss_{sparse} = -\log(\hat{y}_{true}) \dots \dots \dots (5)$$

Description:

1. $Loss_{sparse}$ = Loss value for one sample
2. \log = Natural logarithm (base e)
3. (\hat{y}_{true}) = Probability of model prediction for the correct class.
 - a. Calculation steps of sparse categorical cross-entropy:
 - b. The sparse loss formula is known.

$$Loss_{sparse} = -\log(\hat{y}_{true}) \dots \dots \dots (6)$$

- c. Then, the calculation \hat{y}_{true} is as follows.

$$-\log(\hat{y}_{true}) = Loss_{sparse} \dots \dots \dots (7)$$

- d. Moving the negative sign to be able to calculate \hat{y}_{true}

$$\log(\hat{y}_{true}) = -Loss_{sparse} \dots \dots \dots (8)$$

- e. Calculate the natural logarithm by using base e (2,718).

$$\hat{y}_{true} = e^{-Loss_{sparse}} \dots \dots \dots (9)$$

- f. Then the calculation results are.

$$\hat{y}_{true} = \frac{1}{e^{Loss_{sparse}}} \dots \dots \dots (10)$$

- g. Calculate the final value manually using the Taylor expansion approach.

$$\hat{y}_{true} = \frac{1}{1 + Loss_{sparse}} \dots \dots \dots (11)$$

3.2. System development method

Several methods are used to achieve the expected goals in data collection, including:

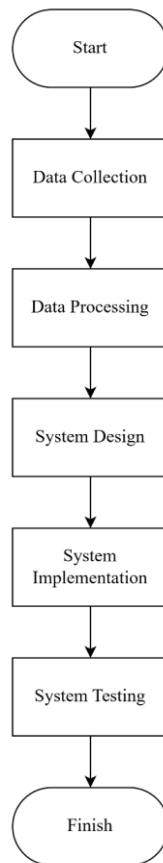


Fig 3. System Development Flowchart

The system development:

1. Data Collection
In this step, the existing data collection on the learning system for 'ula students includes letter, word, and sentence recognition material. Then the nahwu and sharaf science material as a guide to learning quickly the yellow book for 'ula students.
2. Data Processing
At this stage the material data in the yellow book learning media for 'ula students will be processed and entered into Visual Studio Code.
3. System Design
At this stage the author makes a supporting application system for fast learning of the yellow book for santri 'ula to facilitate users in learning wherever and whenever. In designing this system using Visual Studio Code as an initial framework in making this application.
4. System Implementation
At this stage the author conducts several learning media tests to correct errors before system testing.
5. System Testing
Then at this stage, system testing is carried out where users will test whether this learning media is running properly and correctly.

3.3. System Schematic

A system schema is a workflow designed to help explain and illustrate how research is conducted. This scheme is usually in the form of a diagram or visual representation that shows how the research components are interconnected. The following is a system scheme of a school major selection decision support system using the Natural Language Processing (NLP) method.

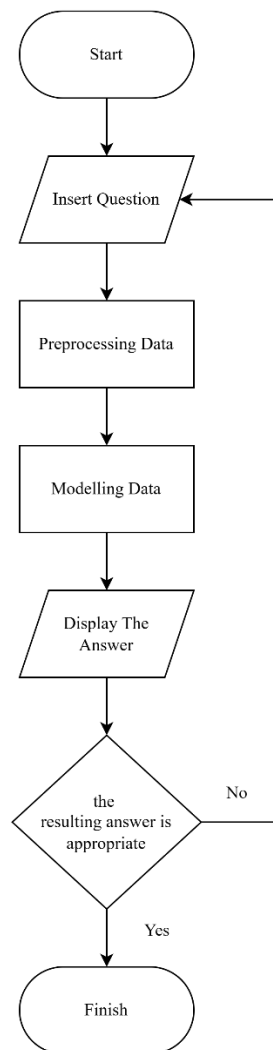


Fig 4. System Schematic

4. Result and Discussions

This discussion is to review the research process; researchers design programs using programming languages, which will then be integrated into the system. Researchers apply several steps in research, starting from data collection, data processing, system design, system implementation, and system testing using the Natural Language Processing algorithm, namely a loss function called Sparse Categorical Cross Entropy.

4.1. Data Acquisition

Data acquisition or collection is made by taking data from web scraping or through books, books, websites, and articles available from the browser. After data acquisition, the data is managed into a dataset in a .json format file.

```

Web_Madidayah > {} dataset.json > { } intents > { } 0 > { } patterns
1  {
2    "intents": [
3      { "tag": "assalamualaikum",
4        "patterns": [
5          "assalamualaikum",
6          "assalamu'alaikum"
7        ]
8      },
9      { "tag": "Waalaikumsalam",
10       "patterns": [
11         "Waalaikumsalam ada yang bisa saya bantu?", "Waalaikumsalam adakah pertanyaan yang ingin ditanyakan?"
12       ]
13     }
14   ],
15   "responses": [
16     "Waalaikumsalam ada yang bisa saya bantu?", "Waalaikumsalam adakah pertanyaan yang ingin ditanyakan?"
17   ]
18 }
  
```

Fig 5. File View in .json Form

The dataset is created manually in the form of a .json file with the following design [18]:

1. *Intents*: a collection of all input and output data used to train the chatbot.
2. *Tag*: Cluster similar text data and use the same as the targeted output to train the neural network.
3. *Patterns*: contains the user's desired input pattern data.
4. *Responses*: contains the output pattern data the chatbot sends to the user.

4.2. Data Preprocessing

Before doing data preprocessing, the dataset must be imported first in the following way [19]:

```
import json
words = []
classes = []
documents = []
ignore_words = ['?', '.', '!']
data_file = open('/content/drive/MyDrive/dataset.json').read()
dataset=json.loads(data_file)
```

Fig 6. Import the Dataset to be Used

Then, data preprocessing will be done for tokenization, lemmatization, and stemming. After data preprocessing, the results will be extracted into 204 patterns, 38 tags, and 33 tokens or unique words.

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt.zip.
204 patterns
38 tags: ["'amil", "'amilma'nawi", "'amilqiyasi", "'amilsama'i", '19hurufpadapembahagian1', '2hurufpadapembahagian3', '
33 token atau kata unik: ['1', '2', '3', '4', '5', '6', '7', '8', '9', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j']
```

Fig 7. Dataset Extract Result

4.3. Data Modelling

The dataset will be trained using the optimizer, activation, and loss functions in this data modelling. The optimizer here uses the Adam algorithm, which functions to reduce loss and improve model performance. The activation function uses Softmax, which calculates the Probability of each class ranging from 0 to 1 [20]. The loss function uses Sparse categorical cross-entropy, which is used for multi-class classification problems where labels are displayed as integers instead of one-hot encoding. Then, we will see the results of the train model by looking at the accuracy value generated through accuracy metrics with a training epoch of 1000.

```
Epoch 995/1000
4/4 ————— 0s 24ms/step - accuracy: 1.0000 - loss: 0.0066
Epoch 996/1000
4/4 ————— 0s 25ms/step - accuracy: 1.0000 - loss: 0.0064
Epoch 997/1000
4/4 ————— 0s 25ms/step - accuracy: 1.0000 - loss: 0.0060
Epoch 998/1000
4/4 ————— 0s 22ms/step - accuracy: 1.0000 - loss: 0.0090
Epoch 999/1000
4/4 ————— 0s 20ms/step - accuracy: 1.0000 - loss: 0.0070
Epoch 1000/1000
4/4 ————— 0s 23ms/step - accuracy: 1.0000 - loss: 0.0061
```

Fig 8. Compile Training Model Results with Epoch Value 1000

In the table below, the training model shows good results every 200 epochs. The loss value provides a smaller value, which indicates that the failure rate of the training model is very low.

Table 1. Model Training Results per 200 Epochs

Epoch	Accuracy	Loss
200	0,99	0,16
400	1,00	0,02
600	1,00	0,01
800	1,00	0,01
1000	1,00	0,00

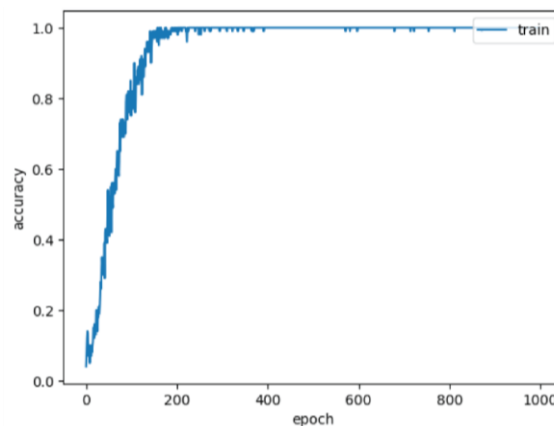


Fig 9. Accuracy Graph of Training Model

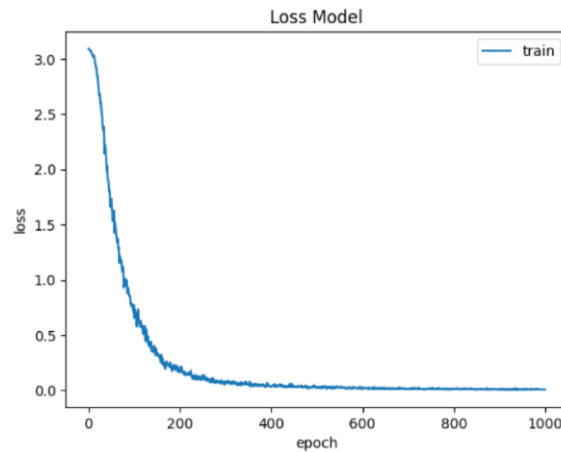


Fig 10. Loss graph of Training Model

4.4. Evaluation

Determining whether a model should be retrained or not is done by confusion matrix testing. The results of this test include accuracy, precision, recall, and f1-score values. The following are the results of testing the model using a dataset of 38 tags.

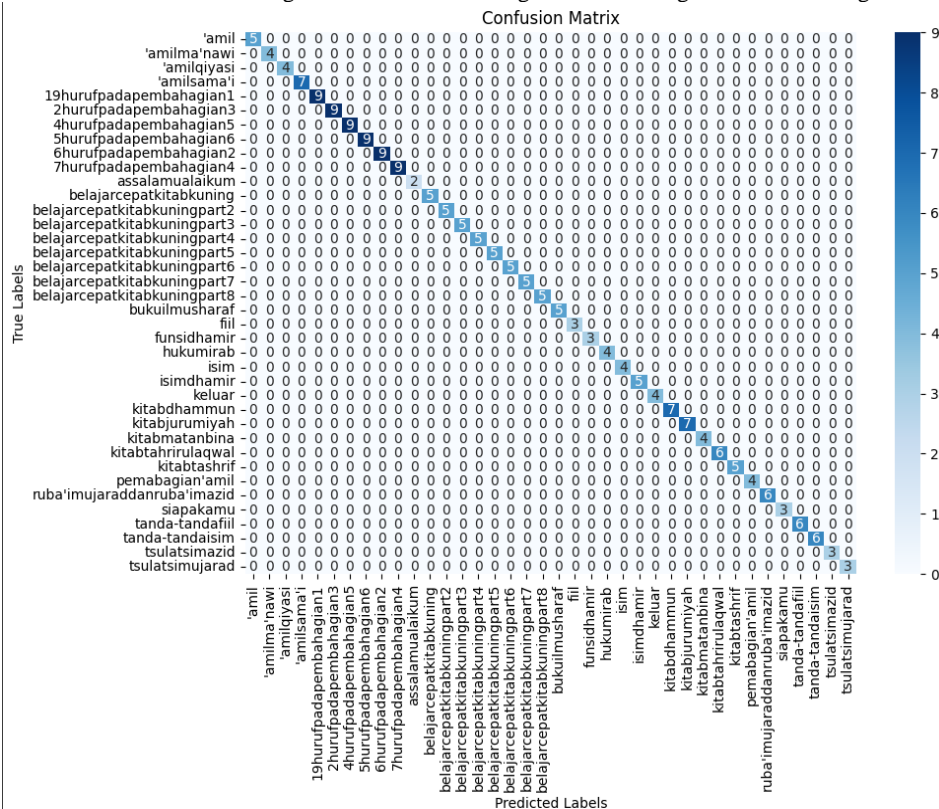


Fig 11. Confusion Matrix Testing Results

The results obtained from the figure above TP (True Positive) are 204, TN (True Negative) are 7548, FP (False Positive) are 0, and FN (False Negative) are 0. The test results produce accuracy, precision, recall, and F1-score values as follows:

$$Accuracy = \frac{204 + 7548}{204 + 7548 + 0 + 0} \times 100\%$$

$$Accuracy = \frac{7752}{7752} \times 100\% = 100\%$$

$$Precision = \frac{204}{204 + 0} = 1,00$$

$$Recall = \frac{204}{204 + 0} = 1,00$$

$$F1 - Score = 2 \times \frac{1,00 \times 1,00}{1,00 + 1,00}$$

$$F1 - Score = 2 \times \frac{1,00}{2,00} = \frac{2,00}{2,00} = 1,00 = 100\%$$

Testing was carried out based on the test data samples used. Thus, the accuracy of confusion matrix classification in identifying objects is around 100%.

In Natural Language Processing calculations, there is a neural network (NN): sparse categorical cross-entropy. This type of loss is used for multi-class classification problems where labels are given in integer form instead of one-hot encoding, like categorical cross-entropy. From the accuracy results produced in the epoch above, namely with a loss of 0.00. Here are the calculation steps of sparse categorical cross-entropy:

1. Known that.

$$Loss_{sparse} = 0,00$$

2. Then, the calculation \hat{y}_{true} is as follows.

$$-\log(\hat{y}_{true}) = 0,00$$

3. Moving the negative sign.

$$\log(\hat{y}_{true}) = -0,00$$

4. Calculating logarithms with base e (2,718)

$$\hat{y}_{true} = e^{-0,00}$$

5. A negative power value indicates the inverse, being.

$$\hat{y}_{true} = \frac{1}{e^{0,00}}$$

6. we will use a simple Taylor expansion approach to calculate manually.

$$\hat{y}_{true} = \frac{1}{1 + 0,00}$$

$$\hat{y}_{true} = \frac{1}{1} = 1,00$$

From a calculation that has been done, the calculation results are obtained with a model accuracy value of 1.00 or 100%, and the value of the loss model is 0%.

4.5. System Implementation Results

The system that has been developed will be tested by implementation to find out how this system runs on computers and other devices. To see the results of the system implementation, see below.

1. Home Page Display

The home page of this application is designed to provide users with an introduction to the purpose and main features of the system. With a simple and intuitive interface, this page displays the main navigational menus, such as the homepage, knowledge list, and chatbot. The design makes it easy for users to understand the application's functions and access the required features easily.



Fig 12. Home Page

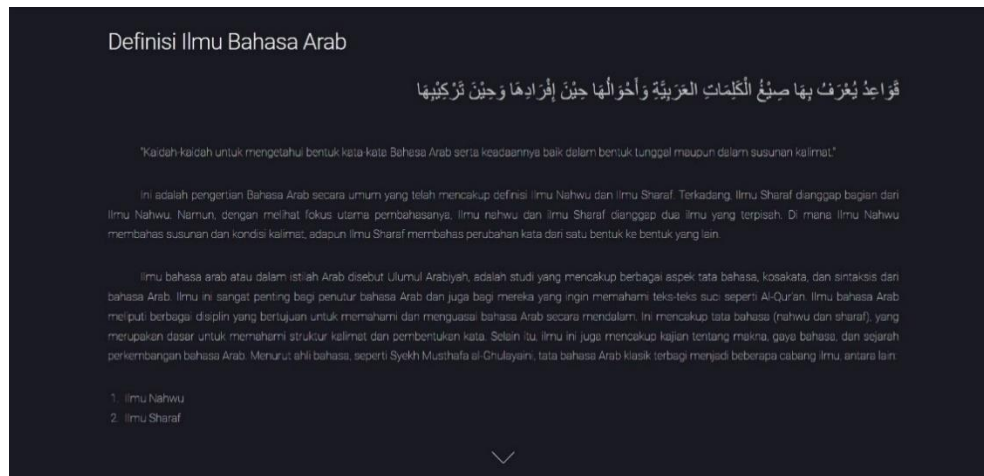


Fig 13. Home Page (Continued)

2. Nahwu Science Page View

The Nahwu page contains basic learning materials on Arabic grammar that are structured to make it easier for students to understand the yellow Islamic classic books. The material is interactive and informative, allowing users to learn nahwu concepts through text explanations, application examples, and simple illustrations.

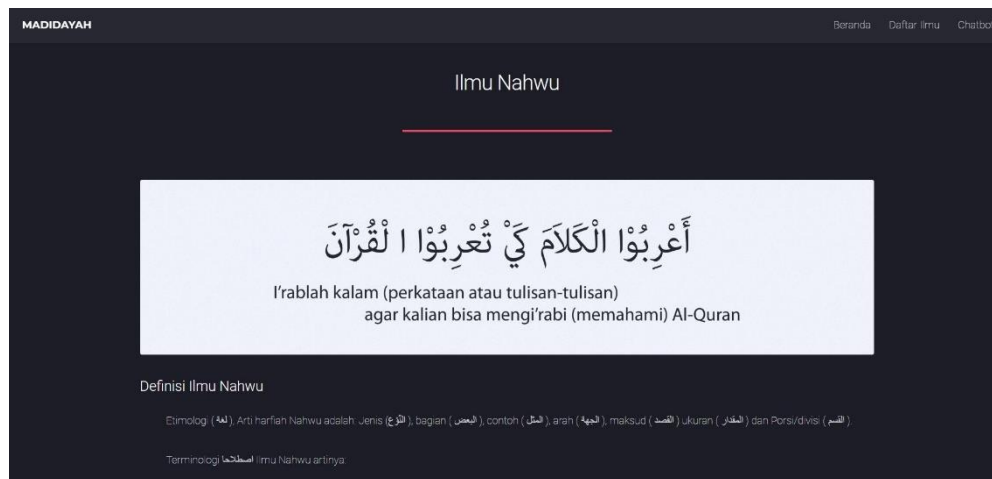


Fig 14. Nahwu Science Page

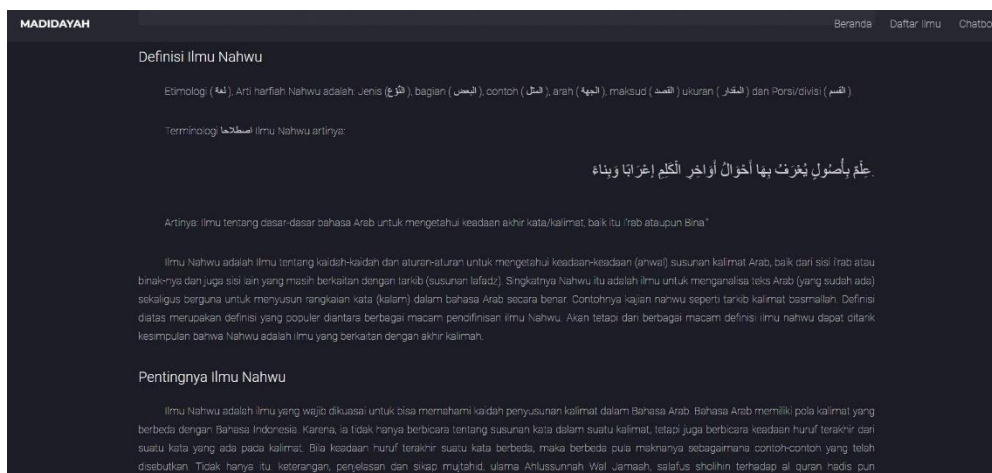


Fig 15. Nahwu Science Page (Continued)

3. Sharaf Science Page View

The Sharaf page offers a guide to learning Arabic morphology, focusing on word changes and patterns. The content includes tables of word changes and in-depth explanations for each pattern used in the yellow scriptures. This page is designed to support an in-depth understanding of the structure of the Arabic language.

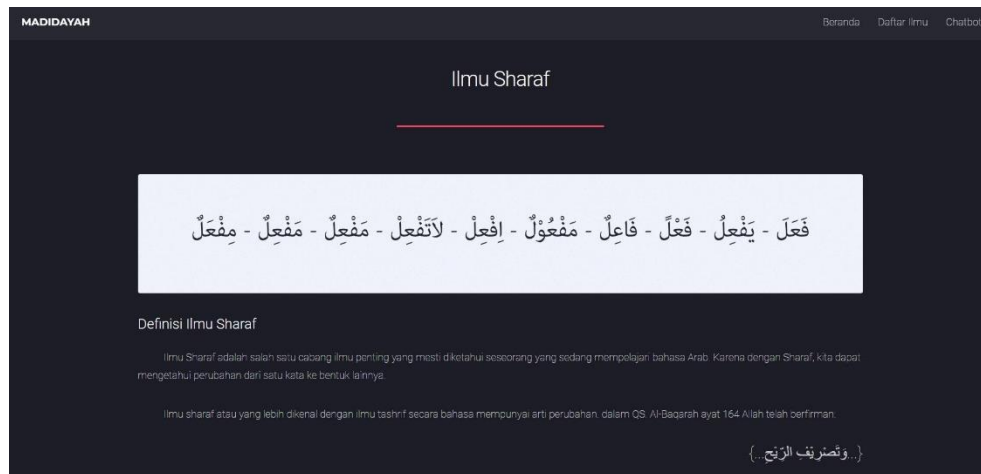


Fig 16. Sharaf Science Page

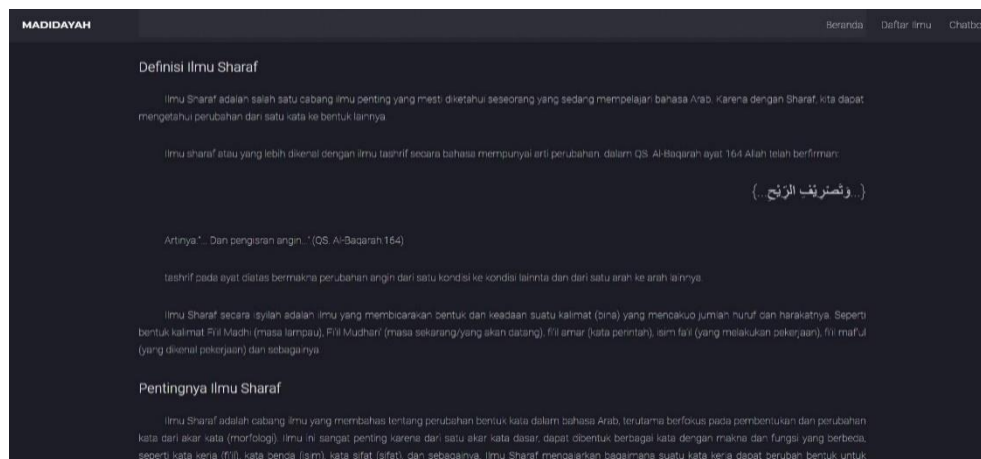


Fig 17. Sharaf Science Page (Continued)

4. Chatbot Page View

The chatbot page is the main feature that allows direct interaction between the user and the system. Through Natural Language Processing (NLP) algorithms, the chatbot can understand the user's questions and provide appropriate and relevant answers based on a trained dataset. This page provides an interactive learning experience where students can ask questions about the yellow book and get instant responses from the system.



Fig 18. Chatbot Page



Fig 19. Chatbot Page (Continued)

5. Conclusion

Based on the results of research on Supporting Applications for Quick Learning of the Yellow Book for Santri 'Ula Using the Natural Language Processing Method that the author uses, the following conclusions can be obtained:

1. The application of the Natural Language Processing (NLP) method has succeeded in providing excellent results by providing a solution for 'ula students so that they are not too bored only reading the material but also provide new experiences in interacting between 'ula students (users) and chatbot.
2. The results showed that learning for 'ula students with the NLP method is very good and easy to understand.
3. The results of applying the Natural Language Processing method provide an excellent accuracy value of 100% and a very low loss value (failure rate) of 0%.

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