IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 2, April 2026, pp. 1211~1218
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i2.pp1211-1218

Deep neural network classification in chatbot system family health counseling services

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Article Info

Article history:

Received Sep 2, 2024
Revised Jan 15, 2026
Accepted Jan 25, 2026

Keywords:

Artificial intelligence
Chatbot
Deep neural network
Mental health
Psychology

ABSTRACT

Mental health problems affect many aspects of life, including physical well-being, work productivity, social functioning, and suicide risk. In Indonesia, access to professional mental health services remains very limited: only a small proportion of people with depression receive treatment and the number of mental health professionals per population is far below international recommendations, creating an urgent service gap. This study proposes an artificial intelligence–based chatbot to support family mental health counseling services in Indonesia. The chatbot uses a deep neural network (DNN) to classify user questions into counseling intent categories and to provide appropriate responses. Psychologists compiled and verified a dataset of Indonesian counseling questions and responses, which was then pre-processed using standard text processing techniques and encoded with a bag of words (BoW) representation. A fully connected DNN with one input layer, two hidden layers of eight neurons each, and a SoftMax output layer was trained using the Adam optimizer (learning rate 0.01) on 80% of the data and evaluated on the remaining 20%. The best configuration achieved a training accuracy of 96%, with test results of 93% accuracy, 92% precision, 93% recall, and 92% F1-score. These findings indicate that proposed DNN-based chatbot can accurately classify counseling intents and generate contextually appropriate responses, suggesting its potential as complementary tool to support initial family mental health counseling in Indonesia.

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1. INTRODUCTION

Mental health is one of life's goals [1]. The majority of the time, abnormal thoughts, emotions, behaviors, and interpersonal relationships are what define mental disorders [2]. Mental health problems affect many aspects of life, including physical well-being, workplace productivity, social functioning, and suicide risk. With mental illness ranking second in terms of documented deaths in 2020 and expected to top the list by 2030, mental health issues are becoming an urgent problem [3].

The main reason 90-95% of people in Indonesia do not have access to better mental health care is the high volume of cases and dearth of experts in this area [4], [5]. Due to a significant shortage of mental health practitioners in Indonesia, the National Riskesdas Report reveals that just 9% of individuals with depression received treatment. As of October 2021, there are only 1,200 psychiatrists in the country, with one psychiatrist for every 250,000 people. There will be 2,917 practicing clinical psychologists by October 2023, with each treating about 90,000 patients. The WHO recommends one psychiatrist or clinical psychologist for every 30,000 people, which is far less than these numbers. The uneven distribution of mental health professionals most of whom are based in big cities exacerbates this deficit [6].

Numerous facets of healthcare, such as illness detection, medical data administration, and patient care tailoring, have been transformed by artificial intelligence (AI). AI enables complex analysis of big data, identification of patterns invisible to humans, and faster and more accurate decision-making [7]. Chatbots for mental health aim to offer real-time emotional support, counseling, and evidence-based advice to users [8].

Deep neural network (DNN)-based AI, which are an evolution of artificial neural networks, possesses a remarkable ability to learn complex data and make accurate predictions or recommendations. DNN can understand and interpret patterns in text data with high accuracy using a deep, multi-layered neural network architecture. This is particularly important in the context of mental health chatbots, where contextual understanding and appropriate responses are key to providing effective support [8]–[10].

In this paper, a chatbot system for family counseling services is developed, utilizing a DNN model with fully connected layers. Psychologists verified the datasets used to train and evaluate the system, ensuring the reliability and relevance of the responses generated by the chatbot. The model's efficacy in producing precise and insightful counseling encounters was assessed using classification report [11], [12].

2. METHOD

The research methodology, as illustrated in Figure 1, adopts a multi-staged framework designed for a secure and robust family health chatbot, integrating advanced natural language processing with a stringent safety infrastructure. The process begins with comprehensive data preprocessing, where raw user queries undergo cleaning and anonymization to preserve privacy, followed by tokenization and stemming to transform linguistic inputs into vectorized features. These features are subsequently processed through a DNN architecture, utilizing dense and dropout layers to optimize pattern recognition while preventing overfitting, with a SoftMax-based output layer facilitating precise intent classification. Central to this methodology is the integration of a regulatory and safety framework that performs real-time risk assessment; queries identified as high-risk or emergencies are immediately diverted to human-led protocols, while general inquiries are cross-referenced with privacy and compliance standards. This systematic workflow culminates in the retrieval of validated health advice, which is then augmented with necessary medical disclaimers to ensure that final response is both informative and ethically compliant with medical communication standards.

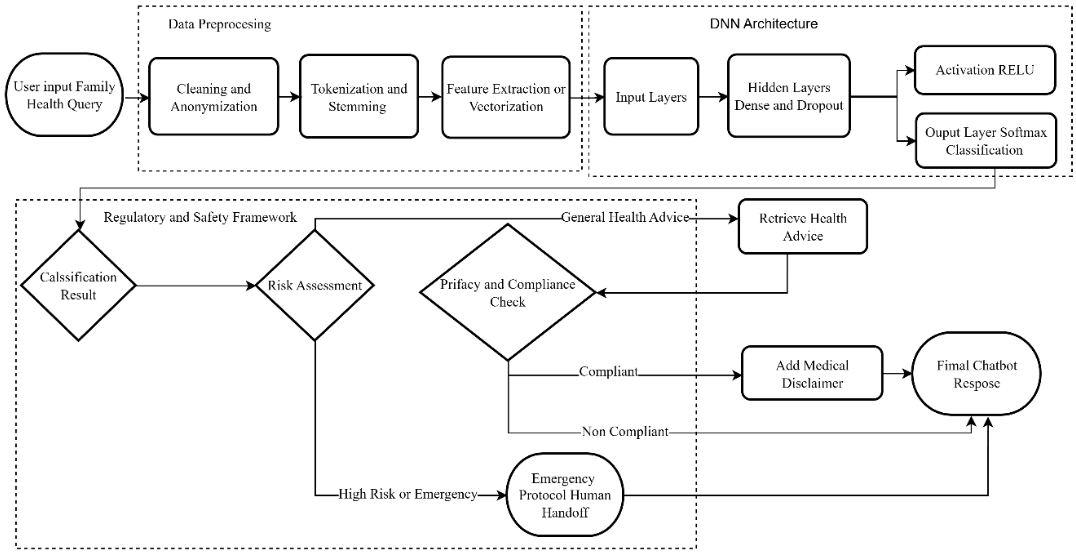

Figure 1. System architecture

2.1. Dataset

The psychologists initially provided the dataset in text form, which then stored in JSON format. The tags were arranged as data labels, the patterns as question patterns, and the responses as answers from each class. The data was preprocessed to transform it from raw data into ready-to-use data. This process involves several steps, including case folding to remove characters other than alphabets, filtering stop word removal to remove meaningless words, and creating a word list to retain phrases with word denotations. Stemming involves transforming words into their basic forms and encoding them using the bag of words (BoW) method. BoW calculates the technique of converting words into numbers based on the frequency of word occurrences in the dataset [13], [14]. The dataset, which has diverse and large properties, is divided into training datasets for model training and testing datasets for model testing, maintaining an 80:20 ratio for each. The psychologists initially provided the dataset in text form, which then stored in JSON format.

This study trained a DNN with one input layer, two hidden layers of eight neurons, and an output layer, using the Adam optimizer with a learning rate of 0.01. Two training durations (500 and 1,000 epochs) and three batch sizes (8, 16, and 32) were experimented with, as summarized in Table 1 [13], [15]. Overall, all configurations reached similarly high training accuracies (96–97%), but several of them showed clear signs of overfitting, visible from the wide gap between training and test accuracy [14]. Models trained with small batches (8 and 16) performed very well on the training data but consistently produced lower accuracy on the test set, indicating that they tended to "memorize" the training examples rather than learn patterns that generalize. Extending training to 1,000 epochs worsened this effect: the model kept improving on the training set while test accuracy stopped improving or even declined, a typical symptom of overfitting on a limited dataset. In contrast, the setting with 500 epochs and a batch size of 32 offered the best trade-off between learning and generalization, reaching 96% accuracy on the training data and 93% on the test data, with only a 3% difference [15]. This moderate batch size likely produced more stable gradient updates than very small batches, helping the model focus on meaningful patterns instead of noise in the training data.

2.2. Deep neural network

The structure of the DNN used in this study is illustrated in Figure 2. At the front, the input layer receives a feature vector derived from the BoW representation of each question pattern, in which every dimension corresponds to the frequency of a particular vocabulary item in the corpus [16]. This vector is then passed to a series of fully connected hidden layers. Specifically, we employ two hidden layers with eight neurons each, equipped with non-linear activation functions to extract higher-level abstractions from the input features [15]. The use of multiple hidden layers allows the network to model complex, non-linear, and hierarchical relationships between linguistic expressions and the underlying psychological constructs in the question, an ability that is essential for discriminating between closely related counseling intents in family mental health settings [17]. The final output layer is a fully connected layer with K neurons, where K denotes the number of counseling tags, and it applies the SoftMax activation function to generate a probability distribution over all intent classes [18]. Overall, this multi-layer design renders the DNN well suited to the intent classification problem at the core of the proposed chatbot system.

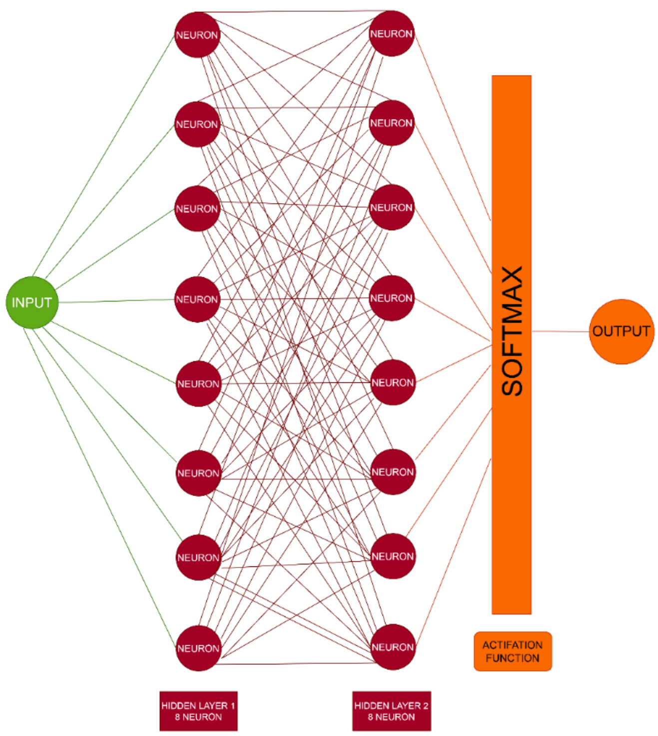

Figure 2. Architecture DNN

A fully connected layer is one in which each layer interconnects with the others [15]–[18]. The input data classification is the responsibility of the fully connected layers. The hidden layer, consisting of eight interconnected neurons, receives the input layer, which includes the training data's feature value vector. In (1) computes the neurons of the first hidden layer.

$$z\_in_i = \sum_{i=1}^{n} x_{ij} \times v_{j+vi} \tag{1}$$

Where v_j is the input, v_i is the bias, z_in_i is the activation of the i-th neuron in the first hidden layer, and x_{ij} is the weight between the i-th neuron in the first hidden layer and the j-th neuron in input layer. The second hidden layer receives the output of the first hidden layer and uses (2) to determine the activity of its neurons.

$$z\_in_i = \sum_{i=1}^{m} x_{ki} \times v_{hi+bk} \tag{2}$$

The second hidden layer uses the same nomenclature as the first layer of concealment [19]–[21]. Lastly, the output layer receives the output from the second hidden layer. Here, the output activation makes use of the SoftMax function and the (3).

$$f(xi) = \frac{Ex(xi)}{\Sigma_j^k = Ex(xk)} \tag{3}$$

The SoftMax function determines the multi-class classification by selecting the class with the highest probability, and its output value ranges from 0-1, with $f(xi)$ representing the probability of the i-th class. The activation of the final hidden layer, as well as the weights and bias applied to the i-th output neuron, combine linearly to produce the value (xi). In the output layer, the value (xi) is subjected to the exponential function Ex, and the resultant value is divided by the exponential sum of all x values for all K classes. This procedure guarantees that all produced probabilities are positive and their aggregate equals 1. This allows the model to select the class with the highest probability as the final prediction, as the SoftMax function provides a probability distribution 1 [22]–[24].

The chosen configuration achieved 93% accuracy, 92% precision, 93% recall, and 92% F1-score, indicating that the DNN can correctly identify most counseling intents while keeping the trade-off between false positives and false negatives at a reasonable level [20]. This performance is consistent with prior studies showing that DNN are effective for health-related classification and chatbot applications, where they frequently equal or surpass traditional machine learning methods such as support vector machines and naïve Bayes, particularly when dealing with high-dimensional text data and complex decision boundaries [22]. Although we did not explicitly implement these baseline models on the same dataset, the obtained results are comparable to deep learning approaches reported in similar domains and suggest that the proposed DNN architecture is competitive with commonly used baselines for intent classification in counseling and medical settings [21], [23]. By using fully connected layers on top of BoW representations, the model can learn non-linear relationships between words and underlying psychological constructs that shallow models often struggle to capture.

2.3. Evaluation model

The confusion matrix of a binary classifier. The actual values are false (0) and true (1), and the predicted values are positive (1) and negative (0). Accuracy describes how accurately the model classifies correctly (4). Precision represents the relationship between the requested data and the model's prediction results (5). The term recall, which is interchangeable with sensitivity, characterizes the recall capacity of the model. Conversely, recall evaluates how well the model detects all true positive examples (6). F1-score, which is weighted average comparison of precision and recall, provides single balanced metric (7) [25]–[29].

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{6}$$

$$\text{F1-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision+recall}} \tag{7}$$

Where TP stands for true positive, which is the model's accurate forecast that the positive class will be positive; TN is real adverse. The negative class was predicted by the model to be negative with accuracy; FP is erroneous positive. When it should have predicted the positive class, the model predicts the negative class as positive; and FN is negative bias. The positive class was incorrectly predicted by the model to be negative.

To ensure that the proposed DNN model generalizes well and does not merely memorize the training data, we employed a structured validation procedure [9]. After splitting the dataset into 80% training data and 20% testing data, we performed internal validation on the training subset using k-fold cross-validation to select the most appropriate hyperparameter configuration (number of epochs and batch size) while keeping the learning rate fixed at 0.01 and using Adam as the optimizer. For each fold, the model was trained on $k-1$.

$\mathrm{k}-1$ folds and validated on the remaining fold, and the average validation accuracy and loss were used to identify configurations that consistently produced stable performance [11]. During training, we monitored overfitting by tracking the evolution of training and validation accuracy and loss across epochs: configurations that showed very high training accuracy but stagnating or decreasing validation accuracy, together with increasing validation loss, were classified as overfitting (as observed, for example, in models trained for 1,000 epochs or with small batch sizes of 8 and 16) [15]. In contrast, the configuration with 500 epochs and a batch size of 32 achieved high training accuracy with only a small gap to validation and test accuracy, indicating a good balance between learning capacity and generalization and therefore was selected as the final model.

3. RESULTS AND DISCUSSION

In this study, we trained a DNN model with an architecture consisting of one input layer, two hidden layers with eight neurons, and regression using Adam's optimization training parameters. We trained each model with a 0.01 learning rate over 500 epochs, and a batch size range of 8, 16, and 32. Table 1 displays the training and testing results.

Table 1. Result training and evaluation model

Epoch	Batch size	Training accuracy (%)	Test accuracy (%)	Result
500	8	97	86	Overfitting
500	16	97	89	Overfitting
500	32	96	93	Great model
1000	8	97	85	Overfitting
1000	16	97	89	Overfitting
1000	32	97	88	Overfitting

From Table 1, the results of each model vary widely, with some showing overfitting, moderate performance, and excellent performance. This shows that parameters such as epoch, learning rate, and batch size greatly affect the model results. There are no fixed rules for setting the values of these parameters, so the parameter values depend on the system's needs and the data's suitability. Of all the training parameters, the best performing model is the one trained using Adam's optimization model with a 0.01 learning rate over 500 epochs and batch size. With a 4% loss, this model's training accuracy is 96%. In the evaluation of test data, the model achieved scores of 93%, 93%, 92%, and 92% out of 100% for accuracy, precision, recall, and F1-score. This implies that it accurately classified 186 out of 200 training data points, with 14 errors. The 3% difference between the 93% testing accuracy and the 96% training accuracy shows that this model is able to complete the classification and does not experience overfitting or underfitting.

The model with the best classification performance is then deployed into the website results in Figure 3. Similar to the system display, the user will input a question, which will then be transformed into vectors using the BoW technique, enabling the DNN model to carry out the calibration procedure. The model will provide an output value from the results of the SoftMax activation function in the form of a value of 0 to 1 to the tag the value closest to 1 will come out as an answer to the question.

To illustrate the practical behavior of the chatbot beyond numerical metrics, we also examined qualitative aspects of its responses in typical family mental health scenarios. The model consistently maps user queries to appropriate counseling intent categories, such as stress management or child behavior and communication, and generates responses that encourage emotional expression, provide simple coping strategies, and suggest seeking professional help when necessary. Overall, the chatbot’s outputs are contextually appropriate and supportive, aligning with the counseling goals defined by the psychologists. This combination of strong quantitative performance and meaningful qualitative behavior indicates that the proposed DNN-based chatbot is suitable for assisting initial family mental health counseling and can serve as a complementary tool to professional services in Indonesia.

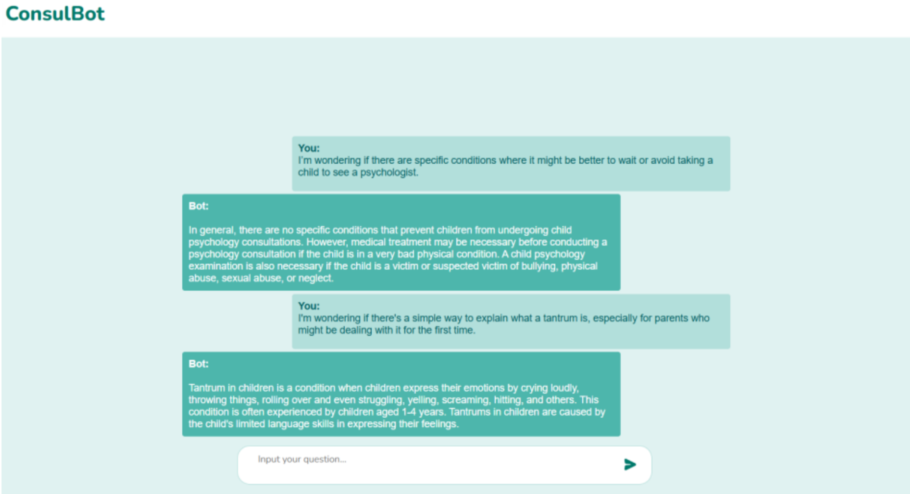

Figure 3. Mental health chatbot application

4. CONCLUSION

Conclude that the DNN approach, when used in the construction of a metal health chatbot application, can provide users with valuable information, aid in initial diagnosis and guide them through their first steps in metal health. The expert-verified dataset and the model's excellent classification ability support this, enabling it to understand diverse question patterns and provide accurate answers. Based on the research findings and analysis, model with a 0.01 learning rate over 500 epochs and batch size and Adam's optimization. The model achieved a training accuracy of 96% and a loss of 4%, with evaluation results of 93% accuracy, 92% precision, 93% recall, and 92% F1-score from a target of 100%. This chatbot model aims to address the issue of access to mental health services in Indonesia by providing AI-based solutions that complement the limited availability of mental health personnel. Given DNN's expertise in managing complex and large data, it is expected that future research will concentrate on creating mental health datasets, allowing the chatbot system to provide broader responses.

ACKNOWLEDGMENTS

First, we thank the psychologists who provided the verified datasets, without which this study would not have been possible. We are also grateful to our academic advisors for their priceless advice and assistance during the investigation. Lastly, we gratefully acknowledge the financial support provided by Universitas Islam Sultan Agung in conducting and completing this study.

FUNDING INFORMATION

This research was funded by Universitas Islam Sultan Agung, Semarang, Indonesia.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Muhammad Ainul Wahib	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known conflicts of interest, either financial or non-financial, that could have influenced the results of this research. This study was conducted independently, and all findings have been presented objectively based on the data and analysis carried out by the research team.

ETHICAL APPROVAL

This research was conducted in accordance with relevant national regulations and institutional policies. The dataset used in this study consisted of counseling question patterns and responses compiled and verified by professional psychologists. All data were anonymized before processing to ensure privacy protection and prevent the identification of individuals. The study followed ethical guidelines for research involving human-related information and complied with the principles of the Declaration of Helsinki.

DATA AVAILABILITY

The data supporting the findings of this study were obtained from various scientific articles related to adolescent mental health. The data were processed and anonymized prior to use in the development of the chatbot system. Due to copyright restrictions and privacy considerations, the data are not publicly available but may be obtained from the corresponding author upon reasonable request

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