Information Processing and Management 60 (2023) 103446

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Multiheaded deep learning chatbot for increasing production and marketing

Shiyong Zheng [a,b], Zahrah Yahya [c], Lei Wang [a,*], Ruihang Zhang [d], Azadeh Noori Hoshyar [e]

[a] *School of Business, Guilin University of Electronic Technology, Guilin 541000, China*
[b] *Management School, Hainan University, Haikou 570100, China*
[c] *Faculty of Computing and Multimedia, Universiti Poly-Tech Malaysia, Malaysia*
[d] *Baoji Vocational & Technical College, Baoji 721000, China*
[e] *Institute of Innovation, Science and Sustainability, Federation University Australia, Brisbane, QLD 4000, Australia*

ARTICLE INFO

Keywords:
Deep neural network
Chatbot
Business product development
Marketing
Artificial intelligence

ABSTRACT

Some businesses on product development prefer to use a chatbot for judging the customer's view. Today, the ability of a chatbot to consider the context is challenging due to its technical nature. Sometimes, it may misjudge the context, making the wrong decision in predicting the product's originality in the market. This task of chatbot helps the enterprise make huge profits from accurate predictions. However, chatbots may commit errors in dialogs and bring inappropriate responses to users, reducing the confidentiality of product and marketing information. This, in turn, reduces the enterprise gain and imposes cost complications on businesses. To improve the performance of chatbots, AI models are used based on deep learning concepts. This research proposes a multi-headed deep neural network (MH-DNN) model for addressing the logical and fuzzy errors caused by retrieval chatbot models. This model cuts down on the error raised from the information loss. Our experiments extensively trained the model on a large Ubuntu dialog corpus. The recall evaluation scores showed that the MH-DNN approach slightly outperformed selected state-of-the-art retrieval-based chatbot approaches. The results obtained from the MHDNN augmentation approach were pretty impressive. In our proposed work, the MHDNN algorithm exhibited accuracy rates of 94% and 92%, respectively, with and without the help of the Seq2Seq technique.

1. Introduction

Chatbots are widely used in markets for receiving feedback from customers. There is a need for intelligent machines to analyze human inputs as the digital world uses digital devices for recording market statistics. Recently, deep learning has played a vital role in data analysis and information processing. Neural networks read and analyze input data with a high level of efficiency. For business development, keeping track of users' requirements and updating products are necessary for the market. The primary motivation behind this research is to develop a chatbot for unlimited user query handling.

The research focuses on developing and implementing a chatbot system to increase production and marketing effectiveness. The

* Corresponding author.
E-mail address: guetwl@yeah.net (L. Wang).

https://doi.org/10.1016/j.ipm.2023.103446
Received 11 January 2023; Received in revised form 9 June 2023; Accepted 19 June 2023
Available online 8 July 2023
0306-4573/© 2023 Elsevier Ltd. All rights reserved.

primary objective is to leverage chatbot capabilities to enhance production processes and improve marketing strategies. Utilizing natural language processing and machine learning techniques, the chatbot intends to provide real-time support, valuable customer insights, and streamline stakeholder communication. The research begins with identifying key areas in production and marketing, drawing on a chatbot system. These areas may include product inquiries, order processing, customer support, personalized recommendations, or feedback collection. The chatbot automates these tasks to improve operational efficiency and shorten response times.

To develop the chatbot system, natural language processing algorithms are employed. These algorithms enable the chatbot to understand and interpret user queries, respond appropriately, and learn from user interactions over time. Machine learning techniques of supervised or reinforcement learning are utilized for training the chatbot model on large datasets, allowing it to handle a wide range of inquiries and adapt to varying customer preferences. The chatbot system is integrated into existing production and marketing platforms such as websites, e-commerce platforms, and mobile applications. This integration ensures seamless interaction between the chatbot and customers, enabling them to access information, place orders, receive recommendations, and resolve issues without human intervention. Furthermore, the chatbot can collect valuable data on customer preferences, purchase history, and feedback, which can be leveraged for targeted marketing campaigns and product improvements.

The effectiveness of the chatbot system is evaluated through various performance metrics, including response time, customer satisfaction, sales conversion rate, and marketing campaign effectiveness. User feedback and satisfaction surveys can also be conducted to assess user experiences and identify areas for further enhancement.

Human interaction with intelligent agents like AI speakers, chatbots, and personal assistants is increased in most growing industries. Due to user-friendly interfaces, the demand for innovative chatbots has increased. The main implication of business growth relays on customer emotions and user feedback. Human-to-machine interaction systems should understand humans' feelings accurately and take necessary actions accordingly. The most awaited model of a chatbot is one able to respond efficiently to random questions and emotions. Emotions can be expressed in various ways, as the same question can be asked differently. The multimodal techniques for human feeling recognition require deep learning models with some innovations (Byun et al., 2021; Jia et al., 2020; He et al., 2019). Simulating the conversation in intelligence-based bot-human chatbot systems has become an emerging issue.

This bot-human conversation is used on mobile and web-based platforms in artificial intelligence. Customers in any organization can easily access these chatbots from their convenient places at any time (Ambika et al., 2021). The chatbot is a simple technology that behaves like a human being to interact with a human user. Artificial intelligence is needed to develop the chatbot with a deep learning algorithm that can ably mimic the behavior of human beings. With the help of a pre-trained dataset, the chatbot helps the user by replying to their queries. Deep learning is one of the most promising technologies for solving many problems in vision and Natural Language Processing (NLP) (Neeraj et al., 2019).

The multi-headed deep neural network (MHDNN) approach proposed in this work has several advantages over existing techniques for addressing retrieval chatbot models' logical and fuzzy errors. Firstly, this approach utilizes multiple heads to capture different input aspects and handle complex interactions between features. It can improve the accuracy and reliability of chatbots and reduce the risk of inappropriate responses to users. Secondly, the proposed model can efficiently retrieve data based on business requirements, allowing more accurate predictions and fewer errors from information loss. This is particularly relevant in scenarios where chatbots are used for product development, and precise predictions are crucial for product success based on user feedback. Thirdly, the MHDNN model reduces the risk of inappropriate responses to users. It is designed to minimize errors in the interaction between the machine and human users using the chatbot concept and the DNN architecture of various headed arrangements.

Existing techniques for chatbot development have some limitations overcome by the proposed MHDNN model. For example, traditional rule-based approaches may not capture the nuances of natural language or be challenging to scale. On the other hand, retrieval-based methods rely on pre-defined templates or search algorithms, which makes them less flexible to handle complex queries or interact with users naturally. Additionally, other deep learning-based approaches may need to be more satisfied with vanishing gradient problems or able to handle long-term dependencies. This will lead to some performance issues arising from current practices in chatbots. To make an effective and reliable solution for chatbot performance improvement, the MHDNN model proposed in this work transcends these limitations by utilizing multiple heads and efficient data retrieval techniques.

In the marketing environment of e-commerce, online transactions are done in the vertical domain-based chatbot to convince users to buy a product. Through chatbots, users can easily interact with the machine, clarify their doubts, and get more information about the product. Therefore, a chatbot is vital in accurately responding to the users' queries and satisfying their requirements through consistent choices between responses. That is a challenging task where a multi-turn interaction chatbot is required in many end-to-end jobs based on vertical domain retrieval. This kind of chatbot uses the architecture of Transformer attention with feed-forward neural (FFN) networks and is suited to performing the task of computer vision. The architecture of the Transformer attention model improves the voice-based interaction of human users with the machine and produces a dependent response on a sequential interaction system (Henderson et al., 2019; Zhao et al., 2019; Wang et al., 2019)

Many research works have implemented the concept of multiheaded chatbots in deep learning algorithms. The remaining issues are handling large numbers of users and keeping track of the chatbot during the interaction. Chatbots can make errors in dialogs and give inappropriate responses to users, thereby reducing the confidentiality of products and marketing. This per se reduces the profit as well as cost complications in enterprises. To overcome these challenges, this paper proposed a multi-headed deep neural network (MH-DNN) for addressing the logical and fuzzy errors caused by the retrieval chatbot model. The main objectives of this proposed work (MH-DNN) are

- Applying the concept of multi-headed attention in the chatbot interaction, the proposed work allows efficient data retrieval based on business requirements. This is critical to chatbot performance as it improves predictions and reduces errors. To minimize the error in the interaction of a human user with the machine via a chatbot, the DNN architecture of various headed arrangements can be used.

- Having more excellent improvisation and conversation skills of a chatbot, the proposed model is analyzed by various error metric measures like error rates of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE).

This paper is written in 5 sections. Section 2 discusses related work on chatbot digital conversation. Section 3 describes the proposed methodology and algorithms. Section 4 provides the result evaluation with outcomes. Section 5 concludes the work.

2. Review of literature

Adopting new technologies in an information system is a business process that needs digital transformation. The digital transformation has been reflected in digital marketing, industries that are necessary to increase production in marketing, including manufacturing, logistics, retail, and other service providers (Miklosik et al., 2019; van der Meulen et al., 2020). In today's world, digital transformation saves time and maintains consistency in production and marketing. However, interaction with a human user is a challenging task for which there are restricted digital devices. Chatbots have solved this restriction by easily interacting via text messages. Chatbots mimic the behavior of human beings and provide users with the experience of interacting with other human users. Developing chatbots is carried out on artificial intelligence techniques, including deep learning. Deep learning algorithms mimic the activities of the human brain, identifying patterns from the training dataset and processing the new dataset in the same way. AI-based deep learning techniques are also used in solving computer vision and Natural Language Processing (NLP) (Beattie et al., 2020; Schuetzler et al., 2021; Moriuchi et al., 2020).

Chatbots are like a messenger, utilized by business people to develop their business activities. In the business environment, a chatbot provides the beginning level of communication between the organization and customers. Chatbots promptly respond to users' queries in an all-rounder-friendly climate to save time and cost for the organization (Garima et al., 2020).

These friendly-based chatbots are used in decision-making in many areas of investing shares, investment, and e-commerce. In the bank, chatbots help to prevent fraudulent activities by managing transactions. In digital marketing management, chatbots analyze the customer's behavior and emotions by monitoring the product and producing a response from the customer. In tourism, chatbots create details for booking hotels, making arrangements to visit tourist spots, searching for flight ticket deals, etc. In e-commerce, chatbots inform various companies of their product details by creating a conversation between a human user and a machine (Abbet et al., 2018; Uñoz, 2018).

Online marketing plays a vital role in our day-to-day activities for planning to buy a product. Before purchasing the product, people want to know about the review of the product. Face-to-face human interaction is not possible for 24/7 service. In that situation, the user can access the chatbot and understand the product details, price, manufacturing details, etc. Therefore, the chatbot is a digital shopping assistant who successfully maintains and manages business activities. It can make communication in real-time and conversation in various ways, like voice notes, a textual input sequence of data, and pop-up windows. Chatbots can serve as virtual assistants to users to improve the relationship between the company and its clients (Luo et al., 2019; Leung et al., 2018).

Based on the working principle, chatbots are divided into two categories rule-based and intelligence-based. While a rule-based chatbot follows the organization's guidelines, an intelligence-based chatbot depends on the dynamics of the social marketing environment (Trappey et al., 2018; Hong et al., 2019; Camps et al., 2018).

The proposed method was evaluated on two publicly available EEG emotion recognition datasets, and the results showed that it outperforms several state-of-the-art methods. This suggests that the self-training maximum classifier discrepancy approach can be an effective method for EEG emotion recognition (Zhang et al., 2023a). The authors proposed modifying CycleGAN architecture in this paper by incorporating semantic and spatial constraints. The semantic control encourages the generator network to produce colorizations consistent with the semantic content of input grayscale image (Li et al., 2023). Experimental results on several benchmark optimization problems showed that the proposed algorithm outperforms several state-of-the-art optimization algorithms regarding solution quality and computational efficiency (Tian et al., 2022). The authors used an atomic force microscope (AFM) to measure surface topography, represented as a grayscale image. The image was then processed using pattern recognition techniques to identify regions of interest (ROI) that contain uncertainties, such as defects or variations in the surface (Zhao et al., 2020). In a multi-agent supply chain system, multiple agents representing different entities, such as suppliers, manufacturers, and retailers, collaborate to optimize the supply chain performance (Li et al., 2020; Guo & Zhong, 2022). The PSO algorithm is a metaheuristic optimization technique that simulates the behavior of a swarm of particles in a search space. The algorithm searches for the optimal values of the SVM parameters, which are critical for achieving accurate predictions (Li et al., 2020).

The paper also highlighted the potential of the e-exhibition industry to support business economic recovery. E-exhibitions provide businesses with a cost-effective and efficient way to reach their target audience and generate sales leads, which is particularly important in the current economic climate (Shang et al., 2023; Cheng et al., 2023). The paper provided several examples of how the proposed model can improve visual reasoning, such as image classification and retrieval (Zheng et al., 2021). The report analyzed trajectory data collected from GPS devices installed in private cars in a specific city. The analysis focused on vehicles' spatiotemporal distribution and travel patterns (Xiao et al., 2023). LBSs provide users with location-based services such as navigation, recommendations, and personalized advertisements based on their location data. However, collecting and using location data raises privacy concerns, as this kind of data can reveal sensitive information about users' activities, interests, and behaviors (Jiang et al., 2021). The proposed framework aims to improve the efficiency and flexibility of task offloading in vehicular edge computing networks using UAVs as mobile edge servers (Dai et al., 2023). To address this issue, integrated sensing and communication systems can be used in UAVs. These systems typically include a variety of sensors of accelerometers, gyroscopes, and magnetometers, as well as communication equipment of antennas, transmitters, and receivers (Zhao et al., 2023). The control input then updates the agent's state toward the desired consensus value. The fixed-time synchronization ensures that all agents reach a consensus within a predetermined period, regardless of the initial conditions or disturbances in the system (Li et al., 2021).

The RBF neural network is an artificial neural network that uses radial basis functions as activation functions (Li et al., 2021). By employing deep invertible networks, DeepMIH overcomes the limitations of traditional steganographic methods that often suffer from degradation of image quality or limited capacity for hiding multiple images (Guan et, 2023). The computer-aided instruction system incorporates convolutional neural network technology of deep learning algorithms commonly used for image and pattern recognition tasks (Cao, 2022). Image enhancement refers to using various editing techniques, filters, or modifications to enhance the visual appeal of images shared by influencers. In the context of product recommendations (Zhang et al., 2023b; Dong et al., 2022). The approach typically involves designing machine learning models, such as neural networks or graph embedding methods (Shen et al., 2021). The event-driven Service-Oriented Architecture (SOA) paradigm focuses on the communication and interaction between different services in a decentralized and loosely coupled manner. In this paradigm, services communicate by sending and receiving events, which represent meaningful occurrences or changes in the system (Cheng et al., 2016). Emotion classification involves identifying and assigning specific emotions or emotional states to text data. Short texts refer to brief and concise pieces of text, such as tweets, social media posts, or text messages (Liu et al., 2023a). Visual question answering involves answering questions about an image, requiring the model to understand both the visual content of the image and the textual content of the question. This task requires the fusion of information from multiple modalities, such as images and text, to generate accurate answers (Lu et al., 2023). Neural machine translation involves training models to translate text from one language to another using neural networks. However, the performance of NMT models heavily relies on the quantity and quality of the training data (Liu et al., 2023b). The scenario considered here involves multiple robot helpers that assist in content caching and delivery within the D2D network (Lin et al., 2022). The optimal segmentation algorithm aims to divide the credit ratings into distinct segments based on the input variables and their relationships with the creditworthiness (Li and Sun, 2020).

3. Proposed methodology

This proposed work describes AI based on deep learning concepts of a multi-headed deep neural network (MH-DNN) for addressing the logical and fuzzy errors caused by the retrieval chatbot model. The workflow of the proposed work is given in Fig. 1.

The multi-headed DNN uses advanced convolution layers to analyze data with high accuracy. The backbone network in the multi-headed concept depends on what the user needs to predict precisely. Then, the convolution layers are used as the prediction heads. The feature extraction is done at a higher level at the backbone network, and each head uses the feature as an optimal input. The loss during training is handled in the prediction head.

Fig. 1 contains four stages, namely, input, pre-processing, chatbot, and output.

3.1. User input

Data is collected from the Kaggle website to analyze the product reviews and increase the company sales and profit.

3.2. Data pre-processing

Natural language processing analyzes textual input information so that the raw input data does not have to be directly fed into the proposed model. Human user languages may be incomplete, inconsistent, and ambiguous. The natural language toolkit (NLTK) is a collection of libraries and programs for symbolic and statistical NLP for writing English in Python. For the pre-processing, this NLTK is described in Fig. 2.

Fig. 2 contains eight stages of the user's input pre-processing.

In linguistics, lemmatization is defined as grouping similarly related words together and reflecting them as a single word. For

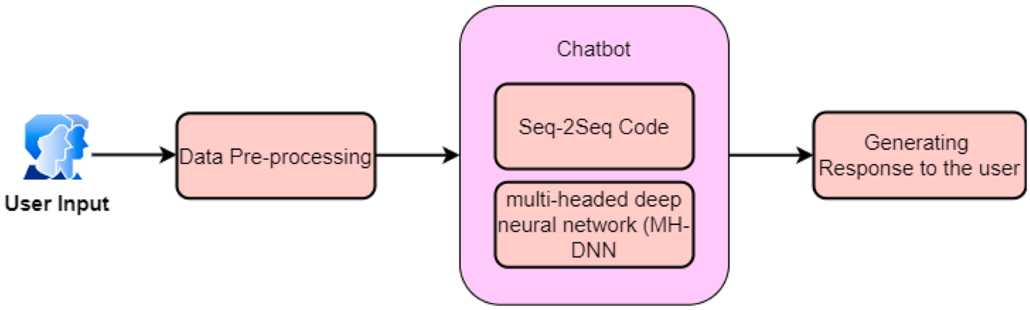

Fig. 1. Workflow of proposed work.

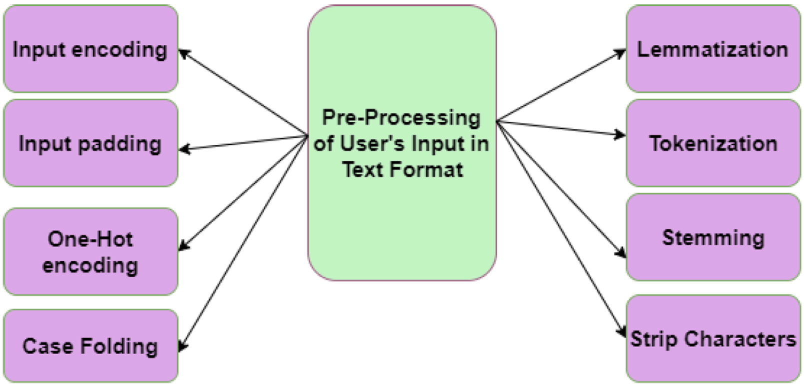

Fig. 2. Pre-processing.

example, walks, walking, and walking are all forms of the word walk. Therefore, the walk is the lemma of all these words. In the tokenization process, the input sentence is split into words named tokens. Next, the stemming process organizes the textual input words into their root and maps a group of words from the same stem. The strip characters step helps to remove irrelevant special characters and punctuation marks. Finally, input encoding is the step where each input token is converted into indexes based on the vocabulary list of text. Input padding arranges the sequence of words into an equal and fixed length. In one-hot encoding, input text words are embedded into "one-hot" code vector binary values in the integer representation. That is where binary-encoded variables replace integer-encoded variables. Table 1 represents the sample of one-hot encoding.

Case Folding: It converts input text into small letters.

3.3. Chatbot

In businesses, chatbots are used to predict product review based on customer responses. The user's query is responded by the chatbot whose framework is given in Fig. 3. User queries exist in two forms of open domain and closed domain. The responses can be either retrieval-based or generative-based.

Open Domain

In an open domain-based chatbot, users can ask any question, which is a challenging problem.

Closed Domain

In a closed domain-based chatbot, users can ask questions about specific sectors or applications. It provides limited responses to digital marketing.

Once a user's query is received, the chatbot needs to ask a question and respond it in two ways. They are retrieval-based systems and generative-based systems.

Responses in the Retrieval based system

The chatbot provides the response based on the retrieval system and follows the heuristic technique for the user query. The concept behind the heuristic approach relies on rule-based machine learning methods. It is easy to implement and does not require much data [7].

Responses in Generative based system

The chatbot provides the response based on the generative model for the user query. It does not depend on a particular sector or application and uses the sequence-to-sequence (Seq2Seq) model to answer the user's query, which makes it harder to implement.

3.3.1. Sequence-to-Sequence model

Translating the user's query into a response by using the Seq2Seq code is called Neural Machine Translation (NMT). It includes an encoder and a decoder with a bidirectional recurrent neural network (BRNN) architecture. This BRNN takes the input sequence of the current and the past data to predict the future. The structure of BRNN is composed of two hidden layers and one output layer. In the NMT, one BRNN is used for the encoder, and another BRNN for the decoder. The encoder sequentially reads the words of the input data and propagates forward.

The decoder predicts the following user's following query based on the previous query.

Table 1
One –hot coding sample.

Product	one-Hot Encoding	**TV**	**Fridge**	**Washing Machine**
TV		1	0	0
Fridge		0	1	0
Washing Machine		0	0	1

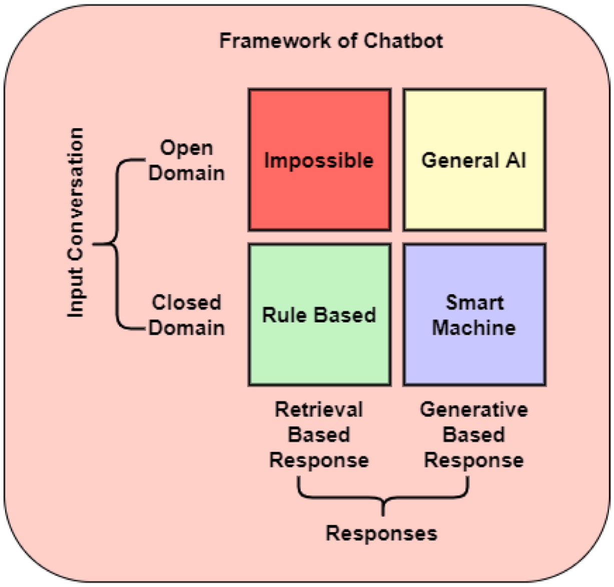

Fig. 3. Framework of chatbot.

3.3.2. *Multiheaded deep neural network (MH-DNN)*

To increase the profit of the enterprise and decrease the error of chatbot conversation with accurate predictions, a multiheaded deep neural network (MHDNN) is implemented. The workflow diagram of the proposed work is given in Fig. 4.

According to Fig. 4, MHDNN receives the user's request, pre-processes it for removing irrelevant information, symbolizes the input sequence of words, and analyzes it using the natural language processing method of the Seq2Seq model. Then, responses are analyzed using a multiheaded deep neural network. The responses from the users produce a better review and more accurate prediction of the product (Baghaei et al., 2022) in the aspect of profit enhancement. The general concept of multiheaded DNN is given in Fig. 5.

The architecture of MHDNN is given in Fig. 5 and starts with the initial input sequence of the chatbot query in vector form. To improve the response to the product review, the weights between the input and hidden layers are updated. It stops its execution until it reaches the minimum error rate. The multiheaded DNN contains the input layer, hidden layers, the output layer, and the activation function. Head 1 of DNN uses the non-linear activation function of ReLU (Rectified Linear Unit) in the hidden layer. Head 2 of DNN uses the sigmoid function as an activation function in the hidden layer. The input sequence of words is represented as a sequence of embedding vector form and then fed up as input to the input layer of DNN. The output layer represents the customer review based on chatbot responses. For the output of these two heads, head 1 DNN and head 2 DNN uses the SoftMax activation function.

The MHDNN parameter is denoted as $\beta = [\beta_1, \beta_2, \ldots \beta_m]$. The layer 1 parameter is $\beta_m = \{w_m, b_m\}$, and the w represents the weight and b represents a bias of m^{th} neuron. The layer l of head 1 DNN is represented in Eq. (1)

$$y_m = \sigma(w_m X_m + b_m) \tag{1}$$

Here, σ- represents activation function, w_m is the weight vector value, X_m represents input neurons, and $b_m$is the bias value. In this head 1 of DNN, ReLU (Rectified Linear Unit) is used as an activation function which is represented in Eq. (2) for each layer except the output

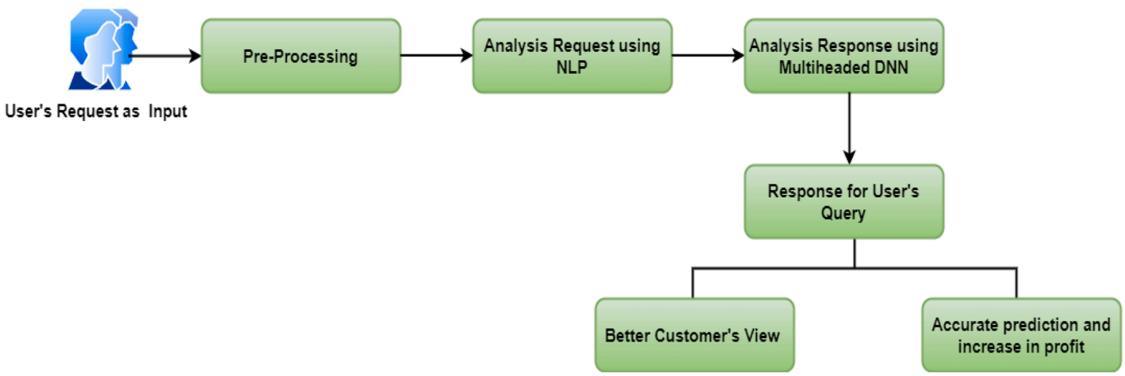

Fig. 4. Workflow of MHDNN.

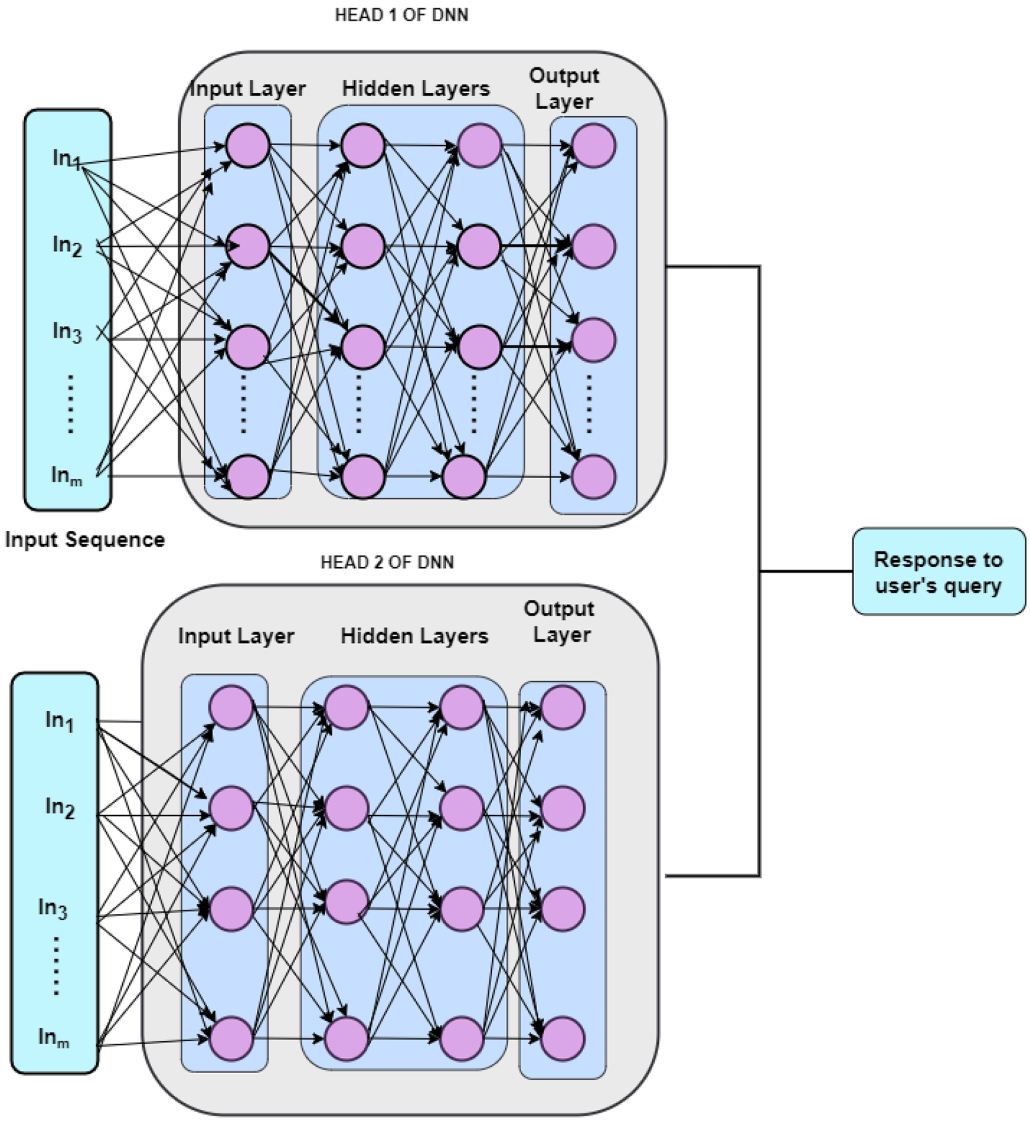

Fig. 5. Architecture of multiheaded deep neural network.

layer. In the output layer, SoftMax activation function is used.

$$\sigma_{ReLU}(X) = \max(0, X) \in [0, \infty] \tag{2}$$

The input user combinations are numbered using the one-hot encoding method and the pre-trained data are sent to DNN data training as numbers. After training, numbers are converted into the original data type. The architecture diagram of head 1 DNN is given in Fig. 6.

Algorithm for MH-DNN

Split the dataset into training, validation, and testing sets.
Define the loss function for each head, reflecting the specific task it addresses (e.g., cross-entropy loss for intent classification, sequence-to-sequence loss for response generation).
Configure an optimizer (e.g., Adam, RMSprop) to update the model's weights during training.
Iterate over the training data in mini-batches and perform the following steps:
Forward pass:
Pass the input text through the shared layers.
Pass the output of the shared layers to each head for task-specific processing.
Obtain the predicted outputs for each head.
Compute the loss for each head using the corresponding ground truth labels.

(continued on next page)

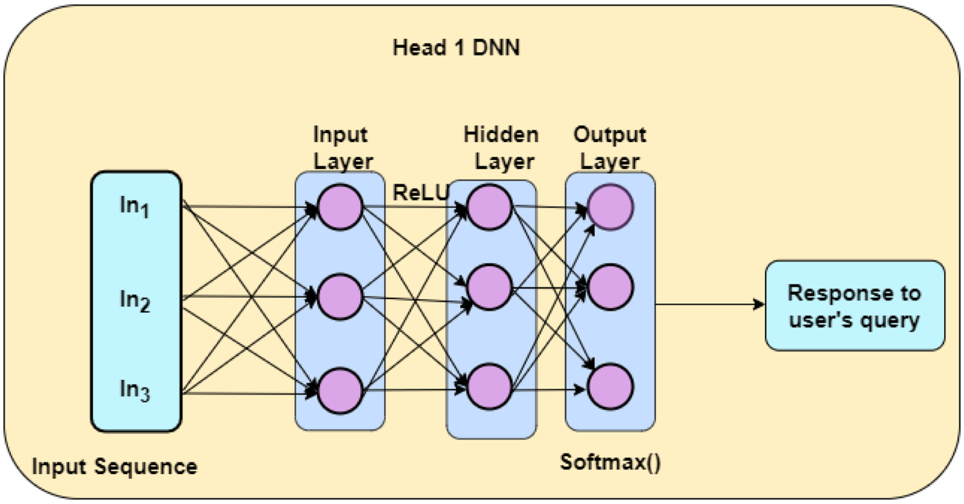

Fig. 6. Architecture of head 1 DNN.

(*continued*)

Backpropagate the gradients through the network and update the model's weights using the optimizer.
· **Model Evaluation and Testing**
Evaluate the performance of the chatbot on the validation and testing sets.
Use appropriate evaluation metrics for each task, such as accuracy for intent classification or BLEU score for response generation.
Iterate and refine the model based on the evaluation results, adjusting hyperparameters or model architecture as necessary.
· **Inference and Deployment**
Deploy the trained chatbot model in a production environment.
Accept user queries as input and process them through the shared layers.
Pass the shared layer outputs to the corresponding heads for task-specific processing.
Generate appropriate responses based on the task outputs and return them to the user.

In Fig. 6, the hidden layer uses ReLU as an activation function and the output layer uses SoftMax as an activation function.

In layer 1 of head 2 DNN is represented as in Eq. (1). The hidden layer uses a sigmoidal activation function as in Eq. (3) for each layer except the output layer. In the output layer, the SoftMax activation function is used.

$$\sigma_{sigmoid}(\mathrm{X}) = \frac{1}{1 + e^{-X}} \in (0, 1) \tag{3}$$

The architecture diagram of head 1 DNN is given in Fig. 7.

In this Fig. 7, the hidden layer uses Sigmoid as an activation function, and the output layer uses SoftMax as an activation function.

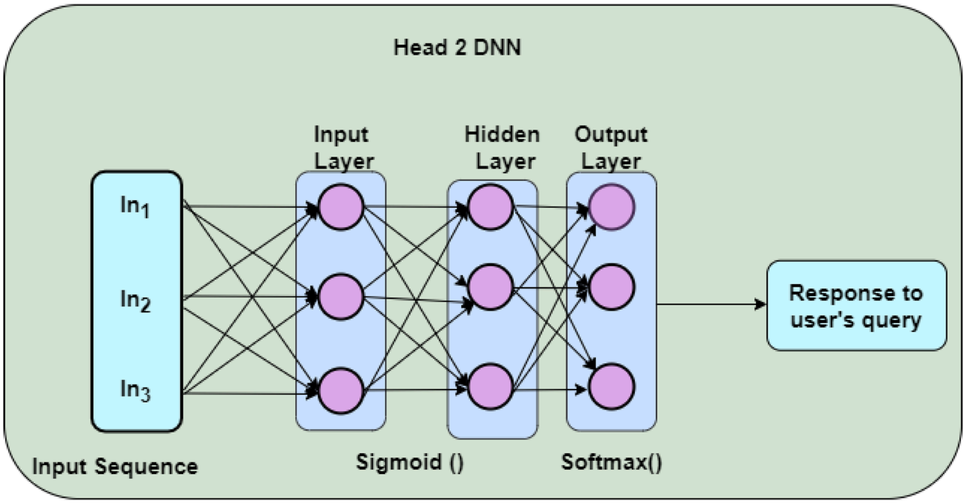

Fig. 7. Architecture of head 1 DNN.

The output layer of head 1 DNN and head 2 DNN uses the SoftMax function as an activation function to improve the accuracy and review of the products from the chatbot queries. The SoftMax function is represented as:

$$\sigma\left(\overrightarrow{X}\right)_i = \frac{e^{X_i}}{\sum_{j=1}^{k} e^{X_j}} \tag{4}$$

Here, σ corresponds to the SoftMax activation function. $\overrightarrow{X}$ is the input vector, e^{X_i} is the standard exponential function for input vector values, and e^{X_j} is the standard exponential function of the output vector.

4. Result & discussion

4.1. Data collection

The data is collected for implementation of the MHDNN model by using Ubuntu Dialogue Corpus [24]. The Ubuntu Corpus is an English dataset that contains multi-turn dialogues constructed from Ubuntu Internet Relay Chat (IRC) logs. This model is implemented using Python 3.6 and Seq2Seq to pre-train word embedding on the training set. The proposed work is implemented by RNN (Lowe et al., 2015; Lakew et al., 2018), Match-LSTM (Wang & Jiang, 2017), and DNN (Garima et al., 2020). Performance metric based on the error rate of the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE). The error rate value is calculated as follows:

Accuracy

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} X100 \tag{5}$$

Precision

$$precision = \frac{TP}{TP + FP} X100 \tag{6}$$

Recall

Recall R at position k in n number of users, and it is denoted as $R_n@k$,

$$R_n@k = \frac{TP}{TP + FN} \tag{7}$$

Here, $R_n@k$is defined as:

$$\frac{\text{number of relevant retrieved response users at top} - k}{Total\ n\ number\ of\ user's\ retrieved\ response}$$

F1-Score

$$F1 - Score = \frac{2\ \times Precision \times Recall}{Precision + Recall} \tag{8}$$

$$MAE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |X(i,j) - Y(i,j)| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N}} (X_i - \widehat{X}_i)^2 \tag{10}$$

MSE

The mean squared error calculates the average of the squares of the differences between the predicted responses and actual responses from the user through the chatbot.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_{pi} - y_{ai}\right)^2 \tag{11}$$

RMSLE

It is a modified version of MSE.

$$RMSLE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\log\left(y_{pi} + 1\right) - \log(y_{ai} + 1)\right)^2} \tag{12}$$

MAPE

The mean absolute percentage error is used to calculate the prediction view in accuracy by representing a relative instead of an absolute error measure.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_{pi} - y_{ai}|}{y_{ai}} \tag{13}$$

In the observation of Table 2, it seems that the precisions of RNN, Match-LSTM, and DNN, respectively reached 89%, 91%, and 87% using Seq2Seq. Our proposed MHDNN algorithm outperformed other algorithms and achieved a precision of 92%. In comparison, the proposed work of MHDNN had the best performance on precision (91%) without Seq2Seq implementation. The RNN, Match-LSTM, and DNN algorithms obtained respective precisions of 90%, 89%, and 86%. Table 3 shows the obtained recall of each algorithm.

In the observation of Table 3, the number of users increases with its relevant responses as the recall metric measures. The recall metric measures of 1 in 2, 1 in 10, 2 in 10, and 5 in 10 were, respectively obtained from various algorithms of RNN, Match LSTM, DNN, and our proposed MHDNN.

Fig. 8 shows the F1-score metric measures of the four algorithms with and without using Seq2Seq.

According to Fig. 8, our proposed work of MHDNN outperformed the others in terms of F1-score metric measure using Seq2Seq.

Fig. 9 shows that the proposed MHDNN model achieved an accuracy rate of 94% using Seq2Seq and an accuracy rate of 92% without using Seq2Seq technique.

Fig. 9 shows that the accuracy rate of various algorithms of RNN, Match-LSTM, and DNN, respectively reached 89%, 90%, and 91% with the use of Seq2Seq technique. In a similar way without the use of Seq2Seq, RNN, Match-LSTM, and DNN models obtained respective accuracy rates of 86%, 88%, and 88%.

Fig. 10 shows the performance metric measures of various error rates.

In the observation of Fig. 10, it seems that the proposed MHDNN model resulted in minimum error rates of MAE of 0.142, MSE of 0.154, RMSE of 0.223, RMSLE of 0.178, and MAPE of 0.184. Compared to other techniques like RNN, Match LSTM, and DNN, our proposed work of MHDNN produced better results.

Fig. 11 shows the computation time for the four algorithms.

The RNN, Match-LSTM, DNN, and MHDNN models, respectively required 12.87 ms, 15.34 ms, 10.89 ms, and 5.22 ms for computation.

4.2. Result discussion

This research performed data analysis on the chatbot for business enterprise applications. Once the product is sold, the customer has various queries about the product. While the computation time of chatbot implementation is not more than 5 s, multi-headed concept is also used to save time and improve accuracy with a reduced error rate. Our model has the advantage of using a standard dataset for evaluation. The convolution algorithms are compared with the multi-headed model. The output evaluation proves that data prediction of the model is done with higher accuracy in a shorter time interval.

The research focuses on the development of a chatbot implemented using a multiheaded deep neural network (DNN). The objective is to create a chatbot that can handle various aspects of conversation processing, such as intent classification, entity extraction, and response generation within a unified framework. To this end, a dataset of conversation examples is collected and pre-processed. The text is tokenized, stop words are removed, and necessary normalization or encoding techniques are applied.

The architecture of the chatbot consists of a multiheaded DNN, which includes shared layers for learning general representations and individual heads for specialized tasks. Each head is responsible for a specific functionality, such as determining user intent or generating appropriate responses. The model is trained using the collected dataset, with specific loss functions defined for each head. An optimizer is configured to update the model's weights during training. The training process involves passing the forward through the shared layers, passing the output to each head, and obtaining the predicted outputs. The loss is computed for each head, and the gradients are backpropagated to update the model weights.

The chatbot performance is evaluated on validation and testing sets with the aid of appropriate metrics for each task. The model is refined based on evaluation results, including adjusting hyperparameters or modifying the model architecture. Once the model is trained and evaluated, it can be deployed in a production environment. The chatbot accepts user queries, processes them through the shared layers, and passes the outputs to the corresponding heads for task-specific processing. The chatbot generates responses based on the task outputs, providing a conversational experience to the users.

5. Conclusion

The aim of this paper is to increase the production and marketing using a multi-headed deep neural network. It receives the input in

Table 2
Shows the implementation of the algorithm with and without using Seq2Seq model.

Algorithm	Precision With Seq2Seq	Precision Without Seq2Seq
RNN	89	90
Match-LSTM	91	89
DNN	87	86
MHDNN (Proposed)	92	91

Table 3
Recall.

Recall	RNN	Match LSTM	DNN	MHDNN
R2@1	66.80%	85.80%	78.90%	88.30%
R10@1	45.10%	64.50%	65.30%	72.50%
R10@2	54.80%	78.80%	58.60%	82.30%
R10@5	71.20%	83.10%	82.50%	91.60%

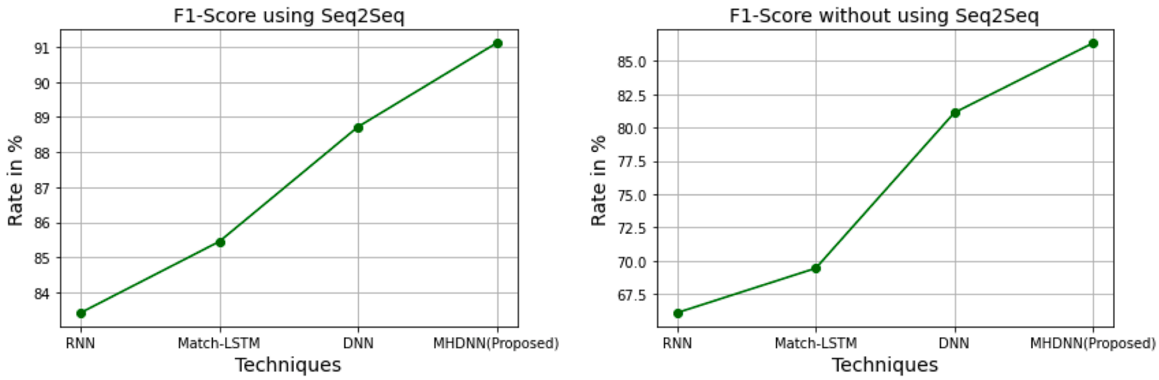

Fig. 8. F1-score.

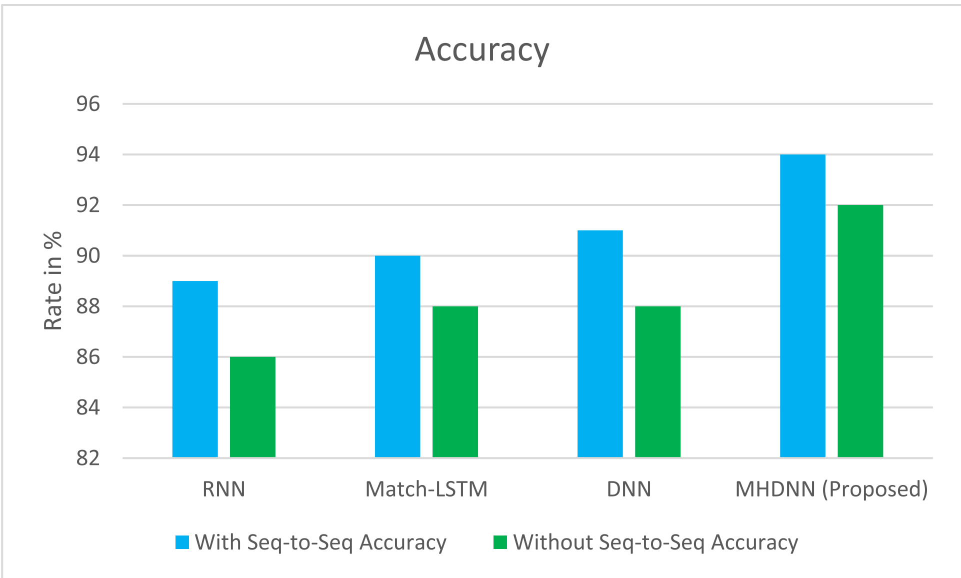

Fig. 9. Accuracy rate.

a query form, undergoes pre-processing, and implements the MHDNN algorithm in the chatbot model. It then produces the response to the particular query. The proposed algorithm is compared with other algorithms of RNN, Match LSTM, and DNN. The accuracy rates achieved 94 and 92% with and without the use of Seq2Seq technique. Compared to other existing algorithms, our proposed work of MHDNN show better results in the aspects of precision, recall, accuracy, and F1-score. The data for implementing the MHDNN model was collected by using Ubuntu Dialogue Corpus. In future works, the model can be extended up to the implementation of complex deep learning techniques considered as an agent to interact with the chatbot.

CRediT authorship contribution statement

Shiyong Zheng: Conceptualization, Methodology, Formal analysis, Supervision, Conceptualization, Methodology, Formal analysis, Supervision, Writing – original draft, Writing – review & editing. **Zahrah Yahya:** Conceptualization, Methodology, Software. **Lei**

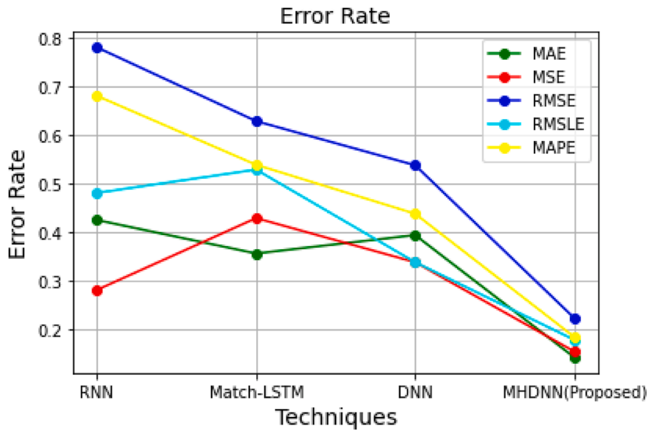

Fig. 10. Error rate.

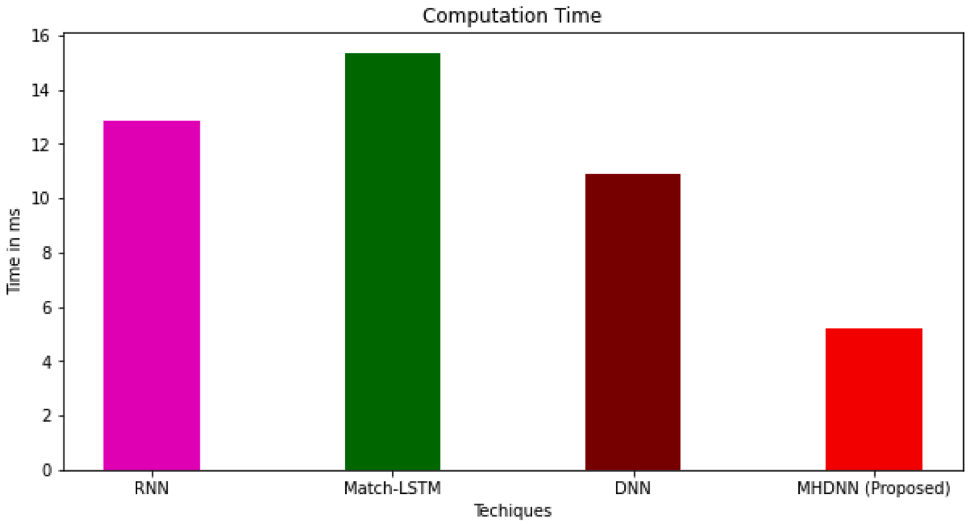

Fig. 11. Computation time.

Wang: Investigation, Data curation, Validation, Resources, Writing – review & editing. **Ruihang Zhang:** Software, Visualization, Writing – original draft, Validation, Writing – review & editing. **Azadeh Noori Hoshyar:** Data curation, Writing – original draft.

Data availability

Data will be made available on request.

Acknowledgement

This work was sponsored by the following funds: "Research on Multidimensional Identification and Long-term Governance Mechanism of Relative Poverty of Farming Households in Border Areas" (Grant No. 20BGL247), General Project of the National Social Science Foundation of China; Research on Branding Strategies for High-Quality Agricultural Development in Ethnic Areas of Southwest China under the "Two Mountains" Theory, General Project of the National Social Science Foundation of China (Grant No. 21BGL129); China Postdoctoral Science Foundation : A study on the mechanism of physician engagement behaviour in online medical communities from the perspective of network effects (No.2022M710038). Guangxi Science and Technology Base and Talent Special Project: Research on the incentive mechanism of user information sharing in live e-commerce - based on social capital perspective (No., 2020AC19034). 2022 Guangxi Philosophy and Social Science Planning Research Project: Path and Policy Optimization of High-Quality Integration of Rural Agriculture, Culture and Tourism for Rural Revitalization (No., 22FGL024). Guangxi 14th Five-Year Education Science Planning Project:No.,2021A033&&No., 2021ZJY1607 && No. 2021ZJY1612&&No., 2022ZJY354&&No., 2022ZJY1699.2022 Innovation Project of Guangxi Graduate Education: (No., JGY2022122).Guangxi undergraduate teaching".

References

Abbet, C., M'hamdi, M., Giannakopoulos, A., West, R., Hossmann, A., Baeriswyl, M., et al. (2018). Intent detection in multilingual chatbot conversations and social media. In *Proceedings of the 22nd conference on computational natural language learning*.

Ambika, Patidar, Koul, Rishab, Varshney, Tanishq, Agarwal, Kaushiv, & Patil, Rutika (2021). AI-based chatbot to solve modern-dayenterprise business problems. *International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), 9*(1).

Baghaei, K.T., Payandeh, A., Fayyazsanavi, P., Rahimi, S., Chen, Z., & Ramezani, S.B. (2022). Deep representation learning: Fundamentals, perspectives, applications, and open challenges. arXiv preprint arXiv:2211.14732.

Beattie, A., Edwards, A. P., & Edwards, C. (2020). A bot and a smile: Interpersonal impressions of chatbots and humans using emoji in computer-mediated communication. *Communication Studies, 71*(3), 1–19.

Byun, S. W., Kim, J. H., & Lee, S. P. (2021). Multi-modal emotion recognition using speech features and text-embedding. *Applied Sciences, 11*(17), 7967.

Camps, D. Chatbot typology., www.inboundcycle.com/blog-de-inbound-marketing/chatbots-marketingestrategia-perfecta, 2018.

Cao, H. (2022). Entrepreneurship education-infiltrated computer-aided instruction system for college music majors using convolutional neural network. *Frontiers in Psychology, 13*, Article 900195.

Cheng, B., Zhu, D., Zhao, S., & Chen, J. (2016). Situation-aware IoT service coordination using the event-driven SOA paradigm. *IEEE Transactions on Network and Service Management, 13*(2), 349–361.

Cheng, C., Yang, X., Jiang, F., & Yang, Z. (2023). How to synergize different institutional logics of firms in cross-border acquisitions: A matching theory perspective. *Management International Review*.

Dai, X., Xiao, Z., Jiang, H., & Lui, J. C. S. (2023). UAV-assisted task offloading in vehicular edge computing networks. *IEEE Transactions on Mobile Computing*.

Dong, C., Li, Y., Gong, H., Chen, M., Li, J., Shen, Y., et al. (2022). A survey of natural language generation. *ACM Computing Surveys*.

Guan, Z., Jing, J., Deng, X., Xu, M., Jiang, L., Zhang, Z., et al. (2023). DeepMIH: Deep invertible network for multiple image hiding. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 45*(1), 372–390.

Guo, Q., & Zhong, J. (2022). The effect of urban innovation performance of smart city construction policies: Evaluate by using a multiple period difference-in-differences model. *Technological Forecasting and Social Change, 184*, Article 122003.

He, J., Li, D., Bo, S., & Yu, L. (2019). Facial action unit detection with multilayer fused multi-task and multi-label deep learning network. *KSII Transactions on Internet and Information Systems (TIIS), 13*, 5546–5559.

Henderson, M., Vulic, I., Gerz, D., Casanueva, I., Budzianowski, P., Coope, S., et al. (2019). Training neural response selection for task-oriented dialogue systems. In *Proceedings of the 57th annual meeting of the association for computational linguistics* (pp. 5392–5406).

Hong, N. J. O., Govindarajan, H., Chien, C. J. C., & Trappey, C. A. (2019). Comprehensive technology function product matrix for intelligent chatbot patent mining. In *Proceedings of the IEEE international conference on systems, man and cybernetics (SMC)* (pp. 1344–1348).

Jia, X., Li, W., Wang, Y., Hong, S., & Su, X. (2020). An action unit co-occurrence constraint 3DCNN based action unit recognition approach. *KSII Transactions on Internet and Information Systems, 14*, 924–942.

Jiang, H., Wang, M., Zhao, P., Xiao, Z., & Dustdar, S. (2021). A utility-aware general framework with quantifiable privacy preservation for destination prediction in LBSs. *IEEE/ACM Transactions on Networking, 29*(5), 2228–2241.

Lakew, S. M., Cettolo, M., & Federico, M. (2018). A comparison of transformer and recurrent neural networks on multilingual neural machine translation. In *Proceedings of the of 27th international conference computational linguistics*, 20–25 August.

Leung, E., Paolacci, G., & Puntoni, S. (2018). Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research, 55*, 818–831.

Li, X., & Sun, Y. (2020). Stock intelligent investment strategy based on support vector machine parameter optimization algorithm. *Neural Computing and Applications, 32*(6), 1765–1775.

Li, Q., Lin, H., Tan, X., & Du, S. (2020). Consensus for multiagent-based supply chain systems under switching topology and uncertain demands. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50*(12), 4905–4918.

Li, D., Ge, S. S., & Lee, T. H. (2021). Fixed-time-synchronized consensus control of multiagent systems. *IEEE Transactions on Control of Network Systems, 8*(1), 89–98.

Li, B., Lu, Y., Pang, W., & Xu, H. (2023). Image colorization using CycleGAN with semantic and spatial rationality. *Multimedia Tools and Applications*.

Lin, Y., Song, H., Ke, F., Yan, W., Liu, Z., & Cai, F. (2022). Optimal caching scheme in D2D networks with multiple robot helpers. *Computer Communications, 181*, 132–142.

Liu, X., Shi, T., Zhou, G., Liu, M., Yin, Z., Yin, L., et al. (2023a). Emotion classification for short texts: An improved multi-label method. *Humanities and Social Sciences Communications, 10*(1), 306.

Liu, X., He, J., Liu, M., Yin, Z., Yin, L., & Zheng, W. (2023b). A scenario-generic neural machine translation data augmentation method. *Electronics, 12*(10), 2320.

Lowe, R., Pow, N., Serban, I., & Pineau, J. (2015). The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *Proceedings of the 16th annual meeting of the special interest group on discourse and dialogue*, 2–4 September.

Lu, S., Liu, M., Yin, L., Yin, Z., Liu, X., Zheng, W., et al. (2023). The multi-modal fusion in visual question answering: A review of attention mechanisms. *PeerJ Computer Science, 9*, e1400.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. Humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*, 937–947.

Miklosik, A., Kuchta, M., Evans, N., & Zak, S. (2019). Towards the adoption of machine learning-based analytical tools in digital marketing. *IEEE Access: Practical Innovations, Open Solutions, 7*, 85705–85718.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2020). Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing*, 1–15.

Singh Kadayan, Neeraj, Dave, Aditya, & K, Vinit. (2019). Chatbot using deep learning. *JETIR, 6*(4). April.

Schuetzler, Grimes, G., Giboney, J., & Rosser, H. (2021). Deciding whether and how to deploy chatbots. *MIS Quarterly Executive, 20*(1), 1–15.

Shang, Y., Pu, Y., Yu, Y., Gao, N., & Lu, Y. (2023). Role of the e-exhibition industry in the green growth of businesses and recovery. *Economic Change and Restructuring*.

Shen, N., D, H., T, Z., Y, L., & M, Y (2021). Modeling relation paths for knowledge graph completion. *IEEE Transactions on Knowledge and Data Engineering, 33*(11), 3607–3617.

Srivastava, G., Agarwal, S., & Vishwakarma, D. (2020). Deep neural network based chatbot. *International Research Journal of Engineering and Technology (IRJET)*.

Tian, J., Hou, M., Bian, H., & Li, J. (2022). Variable surrogate model-based particle swarm optimization for high-dimensional expensive problems. *Complex & Intelligent Systems*.

Trappey, A. J. C., Charles Trappey, U. H., Govindarajan, A., & Sharma, L. C. Y. (2018). Conversational service bot specifications for advanced manufacturing applications. In *Proceedings of the 2018 IEEE international conference on advanced manufacturing (ICAM)*, 16–18 November.

Uñoz, M. Evolution De Los chatbot. https://guelcom.net/origen-chatbots-evolucion-hacia-atencioncliente/, 2018.

van der Meulen, A., Weill, P., & SL, W. (2020). Managing organizational explosions during digital business transformations. *MIS Quarterly Executive, 19*(3), 165. https://www.kaggle.com/datasets/rtatman/ubuntu-dialogue-corpus.

Wang, S., & Jiang, J. (2017). Machine comprehension using Match-LSTM and answer pointer. In *Proceedings of the international conference learning representations* (pp. 2793–2799). Palais des CongrèsNeptune.

Wang, Z.; Ma, Y.; Liu, Z.; Tang, "J. R-transformer: Recurrent neural network enhanced transformer", arXiv:1907.05572, 2019.

Xiao, Z., Fang, H., Jiang, H., Bai, J., Havyarimana, V., Chen, H., et al. (2023). Understanding private car aggregation effect via spatio-temporal analysis of trajectory data. *IEEE Transactions on Cybernetics, 53*(4), 2346–2357.

Zhang, X., Huang, D., Li, H., Zhang, Y., Xia, Y., & Liu, J. (2023a). Self-training maximum classifier discrepancy for EEG emotion recognition. *CAAI Transactions on Intelligence Technology*.

Zhang, Y., Shao, Z., Zhang, J., Wu, B., & Zhou, L. (2023b). The effect of image enhancement on influencer's product recommendation effectiveness: The roles of perceived influencer authenticity and post type. *Journal of Research in Interactive Marketing*.
Zhao, X., Tao, C., Wu, W., Xu, C., Zhao, D., & Yan, R. (2019). A document-grounded matching network for response selection in retrieval-based chatbots. In *Proceedings of the 28th IJCAI conference on AI* (pp. 5443–5449).
Zhao, C., Cheung, C. F., & Xu, P. (2020). High-efficiency sub-microscale uncertainty measurement method using pattern recognition. *ISA Transactions, 101*, 503–514.
Zhao, J., Gao, F., Jia, W., Yuan, W., & Jin, W. (2023). Integrated sensing and communications for UAV communications with jittering effect. *IEEE Wireless Communications Letters*.
Zheng, W., Liu, X., Ni, X., Yin, L., & Yang, B. (2021). Improving visual reasoning through semantic representation. *IEEE Access: Practical Innovations, Open Solutions, 9*, 91476–91486.

Information Processing and Management • Volume 60, Issue 5 • September 2023 • Article number 103446

Document type
Article

Source type
Journal

ISSN
03064573

DOI
10.1016/j.ipm.2023.103446

View more

Multiheaded deep learning chatbot for increasing production and marketing

Zheng, Shiyong[a, b]; Yahya, Zahrah[c]; Wang, Lei[a] ; Zhang, Ruihang[d]; Hoshyar, Azadeh Noori[e]
Save all to author list

[a] School of Business, Guilin University of Electronic Technology, Guilin, 541000, China
[b] Management School, Hainan University, Haikou, 570100, China
[c] Faculty of Computing and Multimedia, Universiti Poly-Tech Malaysia, Malaysia
[d] Baoji Vocational & Technical College, Baoji, 721000, China
View additional affiliations

4 77th percentile
Citations in Scopus

1.17
FWCI

View all metrics >

Full text options Export

Abstract

Author keywords

Indexed keywords

SciVal Topics

Metrics

Funding details

Abstract

Some businesses on product development prefer to use a chatbot for judging the customer's view. Today, the ability of a chatbot to consider the context is challenging due to its technical nature. Sometimes, it may misjudge the context, making the wrong decision in predicting the product's originality in the market. This task of chatbot helps the enterprise make huge profits from accurate predictions. However, chatbots may commit errors in dialogs and bring inappropriate responses to

Cited by 4 documents

Supplier Evaluation in Supply Chain Environment Based on Radial Basis Function Neural Network
Liu, S. , Yu, G. , Kim, Y.
(2024) International Journal of Information Technology and Web Engineering

Evaluating User Performance with Interactive Communication Media Algorithms in Networking Applications
Agarwal, V. , Mahesh, T.R.
(2023) 2023 2nd International Conference on Futuristic Technologies, INCOFT 2023

Enabling Dataspaces Using Foundation Models: Technical, Legal and Ethical Considerations and Future Trends
Timilsina, M. , Buosi, S. , Song, P.
(2023) Proceedings - 2023 IEEE International Conference on Big Data, BigData 2023

View all 4 citing documents

Inform me when this document is cited in Scopus:

Set citation alert >

Related documents

Evolving deep gated recurrent unit using improved marine predator algorithm for profit prediction based on financial accounting information system
Li, X. , Khishe, M. , Qian, L.
(2024) Complex and Intelligent Systems

A Model for Digital Education Management Information System Using Wireless Communication and BP Neural Networks
Wangang, C.
(2023) Mobile Networks and Applications

Intelligent chatbot interaction system capable for sentimental analysis using hybrid machine learning algorithms
Dongbo, M. , Miniaoui, S. , Fen, L.
(2023) Information Processing and Management

users, reducing the confidentiality of product and marketing information. This, in turn, reduces the enterprise gain and imposes cost complications on businesses. To improve the performance of chatbots, AI models are used based on deep learning concepts. This research proposes a multi-headed deep neural network (MH-DNN) model for addressing the logical and fuzzy errors caused by retrieval chatbot models. This model cuts down on the error raised from the information loss. Our experiments extensively trained the model on a large Ubuntu dialog corpus. The recall evaluation scores showed that the MH-DNN approach slightly outperformed selected state-of-the-art retrieval-based chatbot approaches. The results obtained from the MHDNN augmentation approach were pretty impressive. In our proposed work, the MHDNN algorithm exhibited accuracy rates of 94% and 92%, respectively, with and without the help of the Seq2Seq technique. © 2023 Elsevier Ltd

Author keywords

Artificial intelligence; Business product development; Chatbot; Deep neural network; Marketing

Indexed keywords

SciVal Topics

Metrics

Funding details

View all related documents based on references

Find more related documents in Scopus based on:

Authors Keywords

References (50)

View in search results format

All

Export Print E-mail Save to PDF Create bibliography

1 Abbet, C., M'hamdi, M., Giannakopoulos, A., West, R., Hossmann, A., Baeriswyl, M.
Intent detection in multilingual chatbot conversations and social media
(2018) *Proceedings of the 22nd conference on computational natural language learning, Brussels*

2 Ambika, P., Koul, R., Varshney, T., Agarwal, K., Patil, R.
AI-based chatbot to solve modern-dayenterprise business problems
(2021) *International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)*, 9 (1). Cited 3 times.

3 Baghaei, K.T., Payandeh, A., Fayyazsanavi, P., Rahimi, S., Chen, Z., Ramezani, S.B.
(2022)
Deep representation learning: Fundamentals, perspectives, applications, and open challenges. arXiv preprint.

NEW
Check out our new metric to help you evaluate journals!
Dismiss
Learn More

General Information
Web of Science Coverage
Journal Citation Report
Preprint Information
Peer Review Information
PubMed® Information

Return to Search Results

INFORMATION PROCESSING & MANAGEMENT

Share This Journal

ISSN / eISSN **0306-4573 / 1873-5371**
Publisher **ELSEVIER SCI LTD, 125 London Wall, London, England, EC2Y 5AS**

General Information

Journal Website	Visit Site
Publisher Website	Visit Site
1st Year Published	1963
Frequency	Bi-monthly
Issues Per Year	6
Country / Region	ENGLAND
Primary Language	English

Web of Science Coverage

Collection	Index	Category	Similar Journals
Core Collection	Science Citation Index Expanded (SCIE)	Computer Science, Information Systems	Find Similar J
Core Collection	Social Sciences Citation Index (SSCI)	Information Science & Library Science	Find Similar J
Current Contents	Engineering, Computing & Technology	Information Technology & Communication Systems	Find Similar J
Current Contents	Social And Behavioral Sciences	Library & Information Science	Find Similar J
Other	Essential Science Indicators	Social Sciences, General	Find Similar J

Search a topic within this journal

Search a topic within this journal...

Search

Journal Citation Report™ (JCR)

Journal Citation Reports™ 2023

Journal Impact Factor™ (JIF)	JCR SUBSCRIPTION NOT ACTIVE

2022	2021
Not seeing a JIF? A JCR subscription is required to view the JIF for this journal. If this is an error, please use the "Check Subscription Status" button to contact support.	Not seeing a JIF? A JCR subscription is required to view the JIF for this journal. If this is an error, please use the "Check Subscription Status" button to contact support.
Categories: Computer Science, Information Systems | Information Science & Library Science	**Categories:** Computer Science, Information Systems | Information Science & Library Science

Learn About Journal Citation Reports™

Check Subscription Status

Journal Citation Indicator (JCI)

NEW METRIC

The Journal Citation Indicator is a measure of the average Category Normalized Citation Impact (CNCI) of citable items (articles & reviews) published by a journal over a recent three year period. It is used to help you evaluate journals based on other metrics besides the Journal Impact Factor (JIF).

2022	2021
2.39	2.15
Categories: Computer Science, Information Systems | Information Science & Library Science	**Categories:** Computer Science, Information Systems | Information Science & Library Science

Learn About Journal Citation Indicator

Preprint Information

Preprint Policy	From https://www.elsevier.com/authors/journal-authors/policies-and-ethics Multiple, redundant or concurrent publication: An author should not in general... [show more]

Peer Review Information

Type of Peer Review	Single blind
Web of Science Reviewer Recognition	No
Claimed Reviews on Web of Science	956
Public Reports on Web of Science	No
Signed Reports on Web of Science	No
Transparent Peer Review on ScholarOne	No
Transfer Policy	If you agree, your article will be transferred [to participating journals of Elsevier Article Transfer Service] automatically on your behalf with no need... [show more] Visit Site
Reports Published	No

Author Responses to Reviews Published	No
Editorial Decision Letters Published	No
Previous Versions of Manuscript Published	No
Reviewer Identities Published	No
Reviewer Identities Revealed to Author	No
Public Commenting	No
Reviewers Consult with Each Other	No

Create a free *Web of Science profile* to track your publications, citation metrics, peer reviews, and editing work for this journal.

PubMed® Information

Editorial Disclaimer: As an independent organization, Clarivate does not become involved in and is not responsible for the editorial management of any journal or the business practices of any publisher. Publishers are accountable for their journal performance and compliance with ethical publishing standards. The views and opinions expressed in any journal are those of the author(s) and do not necessarily reflect the views or opinions of Clarivate. Clarivate remains neutral in relation to territorial disputes, and allows journals, publishers, institutes and authors to specify their address and affiliation details including territory.

Criteria for selection of newly submitted titles and re-evaluation of existing titles in the Web of Science are determined by the Web of Science Editors in their sole discretion. If a publisher's editorial policy or business practices negatively impact the quality of a journal, or its role in the surrounding literature of the subject, the Web of Science Editors may decline to include the journal in any Clarivate product or service. The Web of Science Editors, in their sole discretion, may remove titles from coverage at any point if the titles fail to maintain our standard of quality, do not comply with ethical standards, or otherwise do not meet the criteria determined by the Web of Science Editors. If a journal is deselected or removed from coverage, the journal will cease to be indexed in the Web of Science from a date determined by the Web of Science Editors in their sole discretion – articles published after that date will not be indexed. The Web of Science Editors' decision on all matters relating to journal coverage will be final.

Clarivate.™ Accelerating innovation.

© 2024 Clarivate   Legal center   Privacy notice   Cookie policy

Manage cookie preferences   Copyright notice   Help