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HK BUDDY : A DEEP NEURAL NETWORK CUSTOM DATA ORIENTED PROFESSIONAL CHATBOT

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ABSTRACT:

The evolving data trends of business ideologies are reflecting the necessity of superlative human - ai interactions. HK Buddy (chatbot) operates on the pre-trained objectified professional data with the fundamentals of humanoid communication. The model developed on the framework of tokenization, padding & label encoding to operate initial functioning. Tensorflow and keras are integrated to design a sequential deep learning model architecture. The basic framework of HK Buddy represents the versatility towards custom prompt data. ROC AUC (Receiver Operating Characteristic Area Under Curve) metric is implemented for performance evaluation. Whereas, the conducted study of existing solutions in literature surveys offers the user - friendly interface. Pragmatic theories demonstrate a prominent level of the accuracy rate of HK Buddy.

Keywords: Data preprocessing, LSTM, Tensorflow, Softmax Activation Function, ROC AUC, Chatbot

1. INTRODUCTION:

In recent years, the rush in the digital conversation path has triggered an escalating want for wise conversational dealers educated in comprehending and addressing consumer inquiries expressed in herbal language. These chatbots, categorized within conversational AI, have emerged as valuable assets throughout a myriad of sectors, encompassing customer service, healthcare, schooling, and e-trade. Through the emulation of human-like interplay, chatbots improve personal engagement, streamline tactics, and supply tailored help, basically reworking the panorama of human-generation interplay.However, notwithstanding the potential inherent in chatbot generation, the improvement and deployment of a powerful chatbot gadget continue to be tricky and multifaceted endeavors. Traditional rule-based total tactics regularly grapple with the intricacies and nuances of natural language, resulting in limited functionality and diminished person delight. Consequently, researchers and practitioners have pivoted towards deep getting to know techniques as a way of cultivating more state-of-the-art and adaptable chatbot fashions.Deep studying, a subset of system mastering stimulated by means of the shape and functionality of the human brain, has exhibited tremendous success across diverseNomenclature herbal language processing (NLP) tasks, spanning language translation, sentiment evaluation, and textual content technology. By harnessing neural networks imbued with multiple layers of abstraction, deep mastering models autonomously collect hierarchical representations of textual records, facilitating the grasp of subtle semantic relationships and patterns.Our studies endeavors to propel the frontiers of the chatbot era by harnessing deep gaining knowledge of strategies to fashion extra wise and responsive conversational marketers. Through the exploration of revolutionary architectures and methodologies, we strive to transcend the constraints of triumphing chatbot systems and redefine the possibilities within human-laptop interaction.At the center of our research lies the aspiration to complement user revel in thru the development of chatbots that exude intuitiveness, informativeness, and engagement. By discerning user purpose and context, our chatbot model targets to supply customized and contextually pertinent responses, thereby fostering more profound interactions and heightening personal pride.In addition to version improvement, our research accentuates the importance of rigorous assessment and validation. We deploy an array of metrics and methodologies to gauge the performance of our chatbot model, encompassing accuracy, precision, recall, and the Receiver Operating Characteristic Area Under Curve (ROC AUC) score. Through quantitative evaluation of the version's efficacy in comprehension and reaction generation, we provide insights into its strengths, weaknesses, and avenues for refinement.Beyond theoretical underpinnings, our research bears practical implications across numerous industries and domains. Chatbots maintain the potential to revolutionize customer service, streamline enterprise operations, and enhance entry to data and offerings. By showcasing the effectiveness of our chatbot model in real-international situations, we aspire to catalyze adoption and innovation in the realm of conversational AI solutions.Industrial oriented chatbots are now specified for their futuristic anomalies, and concluded to be the business factorials as well[3]. This change in the artificial intelligence sector leads us to crucial yet in-development research of deep learning techniques[11]. Deep neural network modules such as, softmax activation function, Loss Function Sparse Categorical Crossentropy and Optimizing class like Adam are endorsed[15]. Recurrent neural networks offer numerous established architectures that provide framework and support to achieve certain chatbot features and objectives.

Long Term Short Memory (LSTM) is a recurrent neural network architecture designed to deal with the long term dependencies in sequence prediction tasks. LSTM solves the data classification and predicting issues for the model. LSTM's strength is its ability to solve intricate problems such as speech recognition and machine translation.Tensorflow and keras operate the functioning of user input and then redirecting for tokenization, padding and tag classification. Generated tokens from user inputs are padded in a sequence to classify according to pre-trained dataset tags and classes. This flow of data results in a precisely trained model for website integration[14].

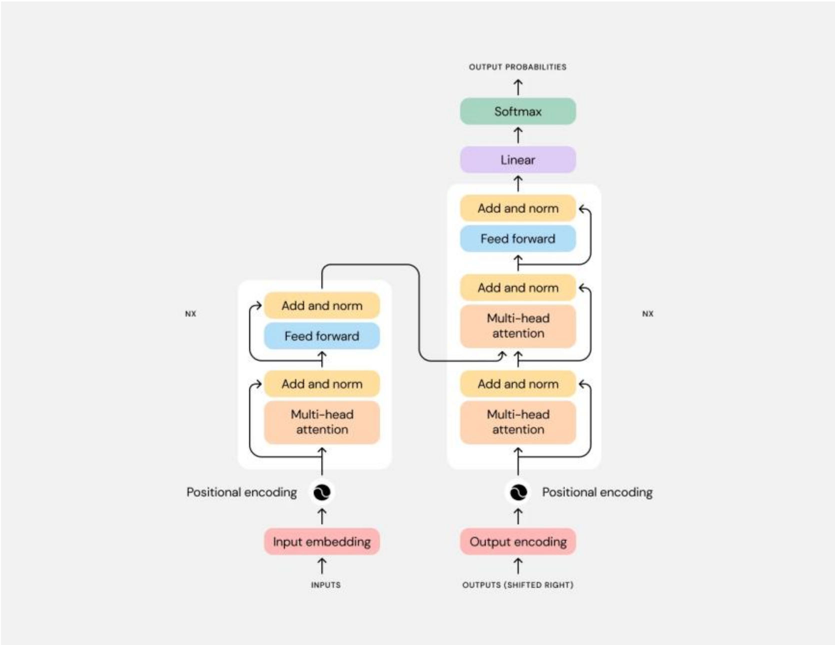

Fig. 1. Softmax Activation and Feed Forward (Deep Neural Network Framework) based chatbot flowchart[1].

The above diagram describes the flow of user input (i.etext or feedback) based chatbot mechanism that operates with linear classification of input tags and softmax activation key of deep learning and the efficiency in the evaluations by training the model on the real time data.
ROC AUC metric is used to evaluate and justify the multiclass - classification of the model to generate accuracy graph and error ratio, according to the user inputs[18]. It is mainly implied to calculate the accuracy of the model and here, the accuracy of the HK Buddy model is observed throughout the training epochs as well as in its testing / implementation phase.

2. LITERATURE REVIEW

The web app integrated chatbots are now in the spotlight for their advanced features like, learning curve, versatility, advanced targeting and segmentation, etc. There are many such major research projects ongoing and developed in this sector. Intercom, Drift, Hubspot Chatbot, Zendesk chat are some of the most efficient and promising existing solutions. Besides, the performance and overall customization independencies these models deal with backlogs that enables the scope of ai at higher levels.

Table -1 Comparative analysis on existing solutions, their pros and cons.

Chatbot Model / Framework	Pros	Cons
Intercom	-Support over multi-channel inputs like email, text and social media. -Advanced Targeting and segmentation.	- Complex understanding learning curve. - Expensive for business with complex customization.
Drift	-Higher engagement perspectives. -Featuring qualitative business chatbot systems.	- Complex configuration setting. - Expensive user packages.
HubSpot Chatbot	-Provides seamless integration with HubSpot CRM -Workflow automation capabilities	- Complex workflow and automation dependent. - Advance features required costly subscription
Zendesk Chat	- Additional Integration support with other Zendesk Products. - Offers Chatbot feature customization	- Limitations in terms of Natural Language Processing. - Customer support dependent.
Chat Gpt3	- Versatile in numerous concepts. - Human language understanding and	- Comparatively offers limited customization options.

	responses.	- Training data dependency and lacking real time data.

Chatbots created with Deep Learning using RNNs were also studied which mostly used BRNNs i.e. Bidirectional RNN[5]. Different techniques and advanced concepts like Natural Language Processing (NLP), Deep Neural Network were studied and a Neural Network which should be used for building HK Buddy was decided[8],[10]. Many chatbots which are made today are built using Open AI API key provides a ready made architecture and reduces the need of developing chatbot from scratch. Also it provides outputs for the inputs which normal chatbots trained on custom data sets don't provide. RNN fails when long sequences of sentences are fed to model, as information needs to be remembered. So an alternative of this needs to be used when working with a dataset containing sequences of sentences. Use Of Json file for storing large dataset is the best way of minimum loss was found in different chatbot models.HK Buddy implies the deep learning techniques i.e., tokenization and padding that generates unique sequences by decoding the user inputs. In simple words, it is an input based chat assistant that is trained on a business website dataset but works on individual based inputs and this increases its reliability and accuracy.

3. METHODOLOGY

This research paper outlines the development and evaluation of a chatbot model using deep learning techniques. The methodology involves 3 major phases:

3.1 Ideation

The ideology is to improvise the mechanism behind the chatbot using multiple framework logics and to train the model on objectified website data. Various Chatbot development frameworks such as Rasa, NLTK, Chatbase, WordPress and Daigflow were studied throughout the process of ideology for the development of HK Buddy Chatbot[9]. The prerequisite of libraries, dataset and other dependencies is as follows:

Software Specifications:

1. 1.Google Colab
2. 2.TensorFlow , NLTK , Matplotlib and other Python libraries
3. 3.Deep Neural Networks
4. 4.CSS and HTML

Use of Natural Language Processing, TensorFlow and use of Deep learning techniques like Deep Neural Network were used in the development of Architecture of HK Buddy Chatbot[17],[12] .Python is the core language used to code the HK Buddy Chatbot model whereas HTML and CSS is used to design web interfaces. LSTM Networks which are the extension of RNNs were used for development of the model.

The rough pathway of HK Chatbot's architecture design implementation through the following steps:

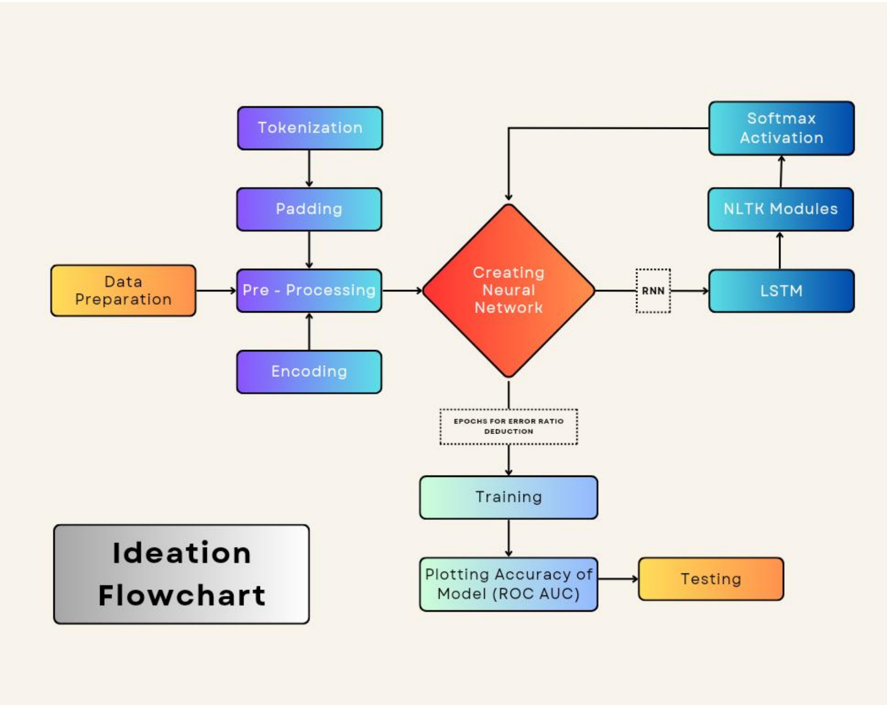

Fig. 2. Chatbot model architectural flowchart and strategic implementation phases.

3.2 Implementation

The implementation of a chatbot involves practical methodologies for developing an intelligent conversational agent. This section details our systematic approach, covering data collection, preprocessing, model development, training, validation, and deployment stages. Utilizing advanced machine learning, particularly deep learning, we aim to create a sophisticated chatbot capable of engaging in meaningful conversations and delivering contextually relevant responses. Emphasizing data quality, model robustness, and user-centric design, our implementation prioritizes transparency, scalability, and usability. By elucidating our approach, we contribute to the advancement of conversational AI research and practice

3.2.1 Importing Libraries:

The python libraries are imported for data preprocessing and architecture designing. The modules such as TensorFlow and Keras are also imported. Other necessary libraries such as NumPy, Pandas, JSON, NLTK are used for data handling and tokenization[7]. Label encoding is a crucial tensorflow module for data classification and it directly affects the ratio of error in model development, and evaluation.

3.2.2 Dataset Importing and Preprocessing:

Raw data is imported in the form of a JSON file consisting of inputs, intents, and tags, accordingly. The initial process involves formation of structured Data Frame by extracting inputs and tags in raw data. The preprocessed supervised inputs and tags are converted into lowercase for standardization of model inputs. Also, other irrelevant data fragments like punctuations are removed.

3.2.3 Tokenization and Padding:

The Tokenization class in TensorFlow uses the sequential decoding and tokenizer for user - input i.e., text[4]. This method converts the input text into numerical sequences. These sequences are padded as per each word for model understanding (this involves binary language communication).In general terms, it's the pivotal stage of human-ai interaction and it is necessary for model training. A series of these uniform padded sequences is later on passed for the label encoding phase.

3.2.4 Label Encoding:

While operating unsupervised data, label encoding technique from scikit-learn module helps models understand featured data in binary language. In this dataframe, the output tags are encoded using the LabelEncoder class. The categorical data transforms into numerical labels required for model training.

3.2.5 Model Architecture Design:

A sequential deep learning model is designed using TensorFlow and Keras. The architecture includes an embedding layer, LSTM layer for sequence processing, and dense layer with softmax activation for multi-class classification[16]. The model is compiled with appropriate loss and optimization functions.

3.2.6 Model Training:

Iterative training process is used to compile the preprocessed dataset in model. Over 200 epochs are defined to train and optimize model parameters and improve predictive performance.

3.2.7 Performance Evaluation:

The trained model's performance is evaluated using the ROC AUC (Receiver Operating Characteristic Area Under Curve) metric[18]. This metric measures the model's ability to distinguish between classes and provides insights into its discriminatory power.

3.2.8. Visualization:

For visualization, matplotlib library in python is imported to demonstrate the accuracy, error/ loss graphs. Then accuracy and loss metrics over epochs are visualized using matplotlib, as per the training history. Additionally, the ROC AUC score is plotted to illustrate the model's performance[18].

3.2.9. Chatbot Implementation:

The trained model is deployed in the backend of the prototype web design, using html. Users can interact with the chatbot by inputting text messages[13]. The chatbot processes the input through tokenization method, then redirects towards the appropriate response tag, and selects a response from the predefined responses associated with the predicted tag. The conversation concludes after the termination signal is generated from user inputs.

3.2.10 Iterative Refinement:

The backend python model undergoes the iterative refinement based on the user feedback and performance evaluation history. This final phase helps the model to enhance its accuracy and response precision in terms of human-ai interactions.This robust methodology outlines the systematic approach used to design, develop, train, evaluate, and deploy the chatbot model, providing a comprehensive framework for replicating and extending the research findings[2].

3.3 Experimentation

The experimentation phase delves into the assessment of our chatbot model's performance, focusing on critical processes such as tokenization, padding, sequencing, and accuracy plotting. This section elucidates our methodological approach to evaluating the efficacy of the chatbot across various tasks

Importing the Data

```
[ ] #importing the dataset
    with open('content.json') as content:
      data1 = json.load(content)
```

```
[ ] #getting all the data to lists
    tags = []
    inputs = []
    responses={}
    for intent in data1['intents']:
       responses[intent['tag']]=intent['responses']
       for lines in intent['input']:
         inputs.append(lines)
         tags. append (intent ['tag'])
```

```
[ ] #converting to dataframe
    data = pd.DataFrame({"inputs": inputs,
                         "tags": tags})
```

```
[ ] #printing the data
    data
```

Fig. 3. Data Importing and Preprocessing of model

A json file is created and imported using python script. For preprocessing the raw imported data, three classes are defined i.e., tags, inputs and responses, respectively. Then, the summarized data is structured using pandas dataframe function.

```
[ ] #tokenize the data
    from tensorflow.keras.preprocessing.text import Tokenizer
    tokenizer = Tokenizer(num_words=2000)
    tokenizer.fit_on_texts(data['inputs' ])
    train = tokenizer. texts_to_sequences(data['inputs'])

    #apply padding
    from tensorflow.keras.preprocessing.sequence import pad_sequences
    x_train = pad_sequences (train)

    #encoding the outputs
    from sklearn.preprocessing import LabelEncoder
    le = LabelEncoder()
    y_train = le.fit_transform(data['tags'])
```

Fig. 4. Data Tokenization, Padding and Label Encoding of model

Tensorflow modules are used for tokenization and other structural methods for dataset, by importing tokenizer class and assigning sequential padding with keras. The sklearn module i.e., label encoder is engaged to fit - transform the generated sequences.

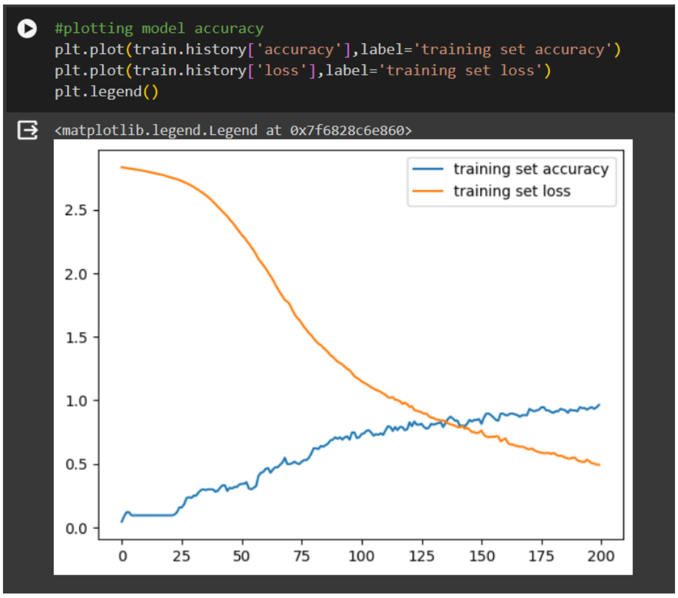

Fig. 5. Accuracy and Loss function graph using Matplotlib

The graph for accuracy and loss function is plotted for over 200 epochs. This graph showcases accuracy of more than 95% in the training phase. The loss function at 200th epoch (standardized number for training the model) is negligible and represents the efficiency of the model. Matplotlib framework of python is implied to visualize the models performance.

4.RESULTS

The experimentation phase and performance evaluation of HK buddy concludes excel communication, human-ai interaction and liability of model architecture.

```
Epoch 195/200
6/6 [==============================] - 0s 5ms/step - loss: 0.5317 - accuracy: 0.9255
Epoch 196/200
6/6 [==============================] - 0s 6ms/step - loss: 0.5185 - accuracy: 0.9379
Epoch 197/200
6/6 [==============================] - 0s 6ms/step - loss: 0.5036 - accuracy: 0.9441
Epoch 198/200
6/6 [==============================] - 0s 6ms/step - loss: 0.5004 - accuracy: 0.9317
Epoch 199/200
6/6 [==============================] - 0s 7ms/step - loss: 0.4932 - accuracy: 0.9441
Epoch 200/200
6/6 [==============================] - 0s 6ms/step - loss: 0.4916 - accuracy: 0.9627
```

Fig. 6. Incrementation of accuracy ratio over epochs.

The pragmatic demonstration of real-time working of HK buddy chatbot is as shown in the below figure.

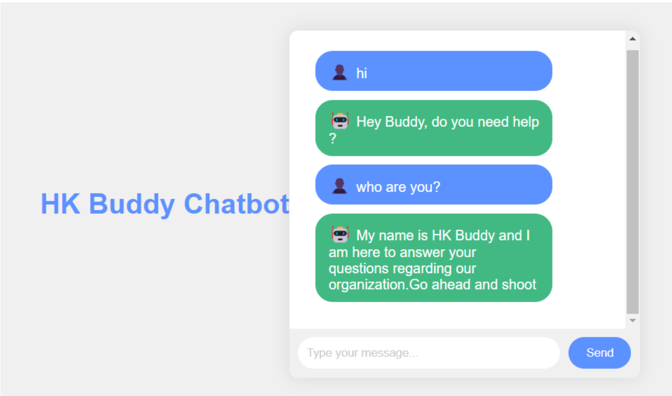

Fig. 7. HK Buddy chatbot working demonstration.

The figure above states the resulting mechanism of the HK buddy chatbot. It is a demo session analyzed by a user in the experimentation stage. Also while accommodating custom data and tags, the error ratio varies with the build of sarcastic tone in user inputs. This sarcastic user input drawback is overcomed with the in-built FAQ (i.e., frequently asked questions) feature in business webpage.

5.CONCLUSION

In conclusion, HK Buddy Chatbot will help the users who visit client websites to know information regarding different Products , Costs and demo services, Company's Founders and Contact details. It will be easier for the users now to get every information with the help of chatbot instead of visiting different tabs on the website. The chatbot is trained using LSTM so our model was able to handle long sequences of sentences as input and output making it better than normal RNNs and also use of SoftMax function and Optimizer the accuracy of model was increased and the loss during training was minimum. HK Buddy Chatbot is your solution for getting information whether it is regarding the company's products or prices of products, Demo services or Contact Details. Now instead of trying to find information on Websites tabs use HK Buddy which will reduce the user's hard work and provide whatever details you want.

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