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SIMPLIFYING BANKING SERVICES USING VOICEBOT

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Abstract:
Helping and guiding customers who are either contemplating making a purchase or are currently making use of a product or service is an essential part of providing good customer service. Consumers expect answers to their inquiries that are both timely and comprehensive. It is essential to the success of any firm to maintain the happiness and contentment of its customers. As a consequence of this, a business has to provide a diverse selection of client services so that customers may choose the ones that are the most appropriate for their requirements. The most frequent forms of customer assistance are telephony, interactive voice response, websites, electronic mail, live chat, and social media. In this work, we resent a banking service voice -bot implicating the overall features based on Deep learning with LSTM hybrid model. The Hybrid design approach indicates Dense, CNN, or BI-LSTM features are integrated into the structural design improvising the overall characteristic features. We enhance the specific features using Lemmatizing of words. With these conditions, we improvise the overall accuracy up to 100% better than existing algorithms as compared.

Keywords: Chat-bot, Voice-bot, Deep Learning, Long short-term memory hybrid model.

I. INTRODUCTION:

A conversational agent that communicates with users via the use of natural language is known as a chatbot. There is a need for several chatbots to fulfill the needs of many different areas. Despite this, chatbots' knowledge bases are hard-coded into their brains by humans. The purpose of this work is to present an overview of the ALICE chatbot, its AIML structure, and our experiments for autonomously building multiple ALICE prototypes based on a corpus technique. Based on the results of our studies, it seems that it may be possible to develop functional prototypes without resorting to complex methods of machine learning or natural language processing. These prototypes have been put to use as tools for a variety of purposes, including the practise of other languages, the visualisation of information, and the answering of questions [1]. The introduction of chatbots as a new disruptive force in the banking industry has altered the manner in which customers connect with one another. The face of the bank-customer contact has been transformed, in particular within the financial sector, as a result of the advent of chatbots that are powered by artificial intelligence. This study investigates whether or not the increased use of chatbots in the banking business is technically feasible. In any nation's economy, the banking industry is responsible for a significant portion of the overall output.

Additionally, it evaluates the most recent chatbot features to see whether or not they can meet the ever-evolving requirements of customers. The idea behind Chabot's is not a novel one. However, during the last several years, businesses have been more interested in the usage of bots. The 1960s saw the inception of the first chatbots, which have gone a long way from their humble beginnings. The rule-based chatbot is the most prevalent form of chatbot, while the artificial intelligence-driven chatbot is considered to be the most sophisticated variety [2].

The most well-known applications of AI to date include natural language processing, machine learning, robotics, and e-service agents, often known as chatbots (see, for example, to [2,4,5]). In particular, chatbot integration into e-services is gaining traction as a potential new approach to enhancing customer support [2,6]. Customers are sometimes disappointed because they have to wait in lengthy contact center lines to speak to a representative of the firm when they have an issue or need information or assistance [7,8]. In a nutshell, their utilization should aim to best suit customers' demands, since doing so is more likely to lead to a good attitude, favorable purchase intention, and loyalty, or, in a word, customer satisfaction [8,9].

II. RELATED WORK

Companies adopt digital channels for customer service, causing complaints due to delays and lack of responses. Foam-Pom Pangasinan faces issues with customer care. Research evaluates an AI chatbot using retrieval-based architecture. Chatbot, based on Dialogflow, selects best responses. Initial USE Questionnaires testing (130 participants) shows positive reception. Future work includes interactive app, regional dialects, voice responses, alternative models, and larger testing. [1].

With the help of natural language processing and an extensive knowledge base, a customer support chatbot is created. LUIS is a conversational AI service available in the cloud that can learn from its users' input. QnA Maker is a FAQ database that can be tailored to your specific needs. This FAQ is great for facilitating conversations with customers. As a result, we provide a smart response and a knowledge base to help you better comprehend and enhance the service by bringing them together. We use the LINE Bot platform to deploy this chatbot. To use it, LINE users need just add the bot's representative. We also use this chatbot to disseminate promotional materials. The studies in [2] indicate that the chatbot is practical and popular among users.

In this research, we introduce an intent matching-based customer services chatbot (IMCSC) that can take over for human sales representatives in customer care situations while maintaining a more humanlike conversational tone by using NLU techniques (NLU). We have incorporated functionality for processing and exporting client orders to a Google Sheet [3], and the bot can answer the most commonly requested inquiries.

Customer service is crucial for business success. E-commerce needs 24/7 support, but human limitations exist. AI chatbots could replace human reps, impacting customer happiness. Chatbots use avatars, speech, text, menus. Text-based chatbots popular, some use deep learning. Advanced chatbots don't always boost happiness. Study assesses chatbot elements: privacy, reliability, personalization, response [4]. Chatbots excel in some quality indicators now.

Helping and guiding customers who have already purchased or are using a product or service is what customer service is all about. Consumers want to have their inquiries answered quickly and thoroughly. The most frequent forms of customer service include telephone, interactive voice response, website, electronic mail, live chat, and social media. The "chatbots" presented in [5] are a novel approach to providing customer care. The article provides an introduction of chatbot technology, a few examples of how firms are using chatbots, and a discussion of the advantages and potential pitfalls of utilising chatbots to improve customer service.

Chatbots are now integral to modern customer support. They're effective in college admissions too. This study combines enrollment and customer service robotics using GPT-2. BLEU evaluates system text quality against reference text. Research proposes AI customer service for college admissions using pre-trained language and response-ranking model [6].

The proliferation of social media has resulted in an increase in the workload for customer service departments everywhere, since even educational institutions feel compelled to maintain many official accounts. One method to prevent this is to use a chatbot, which may improve productivity while also providing helpful solutions to customers' inquiries. The chatbot used for this research was built with the use of the Telegram API and the webhook technique. Other from that, the users (here, the kids), the administrator, and the chatbot all communicate through Telegram Bot. All of the chatbot's features have been successfully tested with little effort [8].

AI and machine learning power human-like chatbots for customer assistance. Chatbot use is common in customer care platforms. They enhance service in modern contact centers via text or speech interaction. Call center crowding and staffing challenges are addressed by incorporating chatbots. Article quantitatively analyzes a contact center with both chatbot and human options. Model uses Markov process, stationary probabilities, and state equations. Proposed algorithm estimates performance metrics. Chatbots reduce overload, improve contact center performance [10].

AI, ML, and DL enable robots to mimic human abilities. Chatbots use AI and NLP to simulate human interaction. Article explains chatbot workings, creation methods, evaluates current options. 75% customers face poor service, chatbots aim to improve responses. Seq2Seq AI Chatbot designed with encoder-decoder attention, using LSTM cells. Goal: chatbot like a human buddy for off-topic convos. Model adaptable to diverse datasets [11].

Tourism combines various technologies for digital assistance in all trip phases. AI's progress, like Chatbots, is transforming travel. Article discusses AI advancements' impact on the industry. Research involves Coimbatore client preferences and chatbot creation. Chatbot covers What, How, Where for city info. Digitization makes travel easier, more affordable, and offers virtual tour guide capabilities [12].

This study investigates how system features and individual user traits influence how people evaluate and rely on a service. In this paper, we build a trust research model for AI chatbots using the social presence theory. The primary findings reveal that users' perceptions of personalization, media richness, and prior usage experience positively affect their social presence, while users' perceptions of cognitive reactance have a negative effect on their social presence, and users' social presence positively affect their trust in the system. This research offers useful technological enhancement and marketing recommendations for managers [13] by examining the factors impacting trust.

An application with a conversational interface mimics a human technical support agent by conversing with users in their native language. The objective is to provide consumers with standard, low-cost, and quick replies while keeping customer service expenditures to a minimum. In this paper, we introduced a chatbot-based live customer assistance system among other features. Open Campus, a provider of free and open online courses, is where you may find the chatbot in action. If the suggested design works, it might be used by many other types of educational institutions, including Open Educational Resource and Massive Open Online Course (MOOC) providers [14].

In the digital age, chatbots save time for customers and support staff. IslamBot answers Islam-related queries using English Islamic Articles dataset (EIAD). EIAD includes 10,000 English Islamic publications from sources like NewMuslims.com, IslamReligion.com, and IslamQA.com. Dataset structured, labeled, with 15 types of information and various subjects. Study focuses on EIAD collection process [15].

Chatbot design relies on natural language processing (NLP), with NLU and NLG subdomains. NLU aids conversational user interface creation, using Intent Classifier and NER subcomponents. Both developed with neural networks and optimization techniques. NLG offers relevant responses using intent, entities, knowledge base, and other modules.

More information improves Chatbot intelligence. Generating human-like conversations is challenging due to data scarcity for training. Earlier chatbots like Alice used rule-based AIML. Recent efforts automate knowledge base generation. This article manually constructs a knowledge base for neural network training, similar to RASA format. JSON format used, containing Input and Response sections. Input includes user messages, sender's intent, and entities. Entities aid user query understanding.

Users report incidents online, receiving unique reference numbers. Web interface or customer support channels used. Meta-data like time, description, tags are stored in a standard format. Customer service reps use web tool to review and respond. Agents consult resources to resolve issues, can update or escalate tickets. Many reported problems share common themes, allowing automation. Chatbots can enhance customer service, providing fast and accurate responses, outperforming humans.

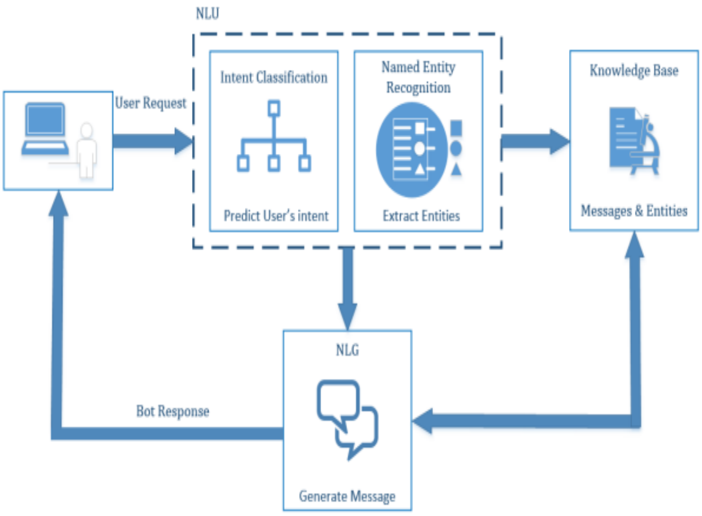


Figure 1: Representing the overall Chat bot block diagram with learning models[2]

III. PROPOSED METHODOLOGY:

The main aim of proposed work is to implement the patterns recognition functionality with the deep learning feature indicating the overall responses observed while estimating the overall changes customer reviews and its sentiments. So, as to create such model we have implored multiple datasets indicating the acquisition of the dataset for which real time dataset based on Json file was chosen. As per the block diagram we have depicted the importance of file format for which the model implementation is applied. So, the first block of the design model diagram shows the acquisition of the dataset from the Kaggle website to the local directory indicating the overall effectiveness of the dataset. We pre-process the data depending upon the type of User responses with its sentiments/(reviews) with functional transformation process of TF-IDF vectorizers or custom User defined functions to implicate the overall words and sentences count. While the reading of the data is performed with panda's library, with read_csv function, but the feature extractions are defined with the tags associated with each type of users and their choices of response based on the similarity work counts and similar sentence representation from TF-IDF vector's.

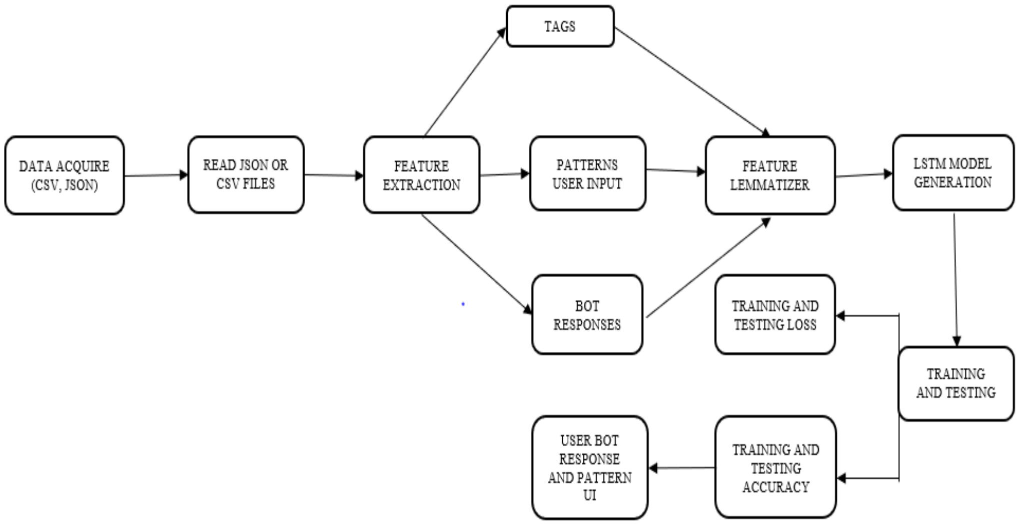


Figure 2: System Architecture

After these features extracted process, we tend to implicate the model based on LSTM indicating the overall design feature acquisition based on its training and testing accuracy of the design. The solution of the tokenized answers for the user-defined and bot responses are clustered with specific embedding process based on Encoder -Decoder model for the LSTM design. To design the encoder we have approached conditional parametric for each of the input and output layers for Encoder. For the input layer case the overall parameters required to create the LSTM model is given by:

a) Maximum length of query: N_query for users
b) Embedding Layer: Vocabulary size : Can be varied from 100-1000 depending upon the maximum length of the query.
c) Similarly, for the decoder case also:
d) Input layer: Maximum length of query: N_query for users
e) Embedding layer: Vocabulary size: Can be varied from 100-1000 depending upon the maximum length of the query.
f) Finally, a collective model for the both encoder and decoder structure indicating the overall design model.

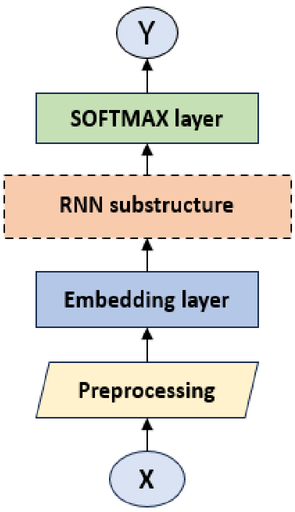


Figure3: representing the overall RNN layer for the current design with LSTM [10]

Pre-processed design conditions, denoted by input 'X,' are the focus of this analysis. For this, we treat each sample word as its own token and do an index mapping to compare it to our master vocabulary. An embedding layer transforms the starting point of the sequencing into denser matrices of a constant size. Parsing this set of embedded vectors into the recurrent neural network framework. The last step involves feeding the RNN's result into a softmax layer, where the softmax function is used to display the likelihood distribution across the RNN's output classes. The same structure design with LSTM approach:

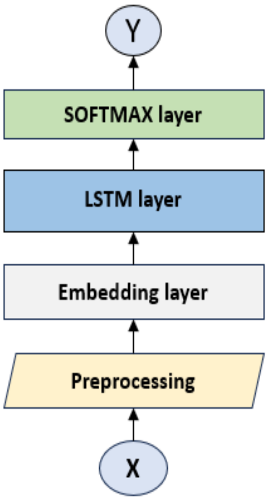


Figure 4: Representing the overall LSTM layers to realize the effectiveness of the proposed design [11].

The overall flow model with types of layers utilized in LSTM is shown above. We observe that the overall changes on the layer at the output layer as the activation functions which are effective based on the design when Tan-h or sigmoid or soft-max are utilized. In most of the cases soft-max and Tan-h layers are used. In our design we postulate the differences on the layers and its importance with its size indicating the overall time consumed with loss and accuracy.

ALGORITHM:

ILSTM:

As shown in the below figure, the overall structure of the layers utilized in are mention in the section IV-2 indicating the type of RNN and its layers. Presently, in our design we utilize two layers of LSTM, 6 layers of dense model indicating the overall model with effective loss calculated based on softmax layer. The overall formulative models for each of the layers utilized are mentioned in the algorithm indicating the performance metrics as loss.

ALGORITHM 1:

Input: $X_i, W_i, w_i, b_i W_f, S, W_o,$

Output: C_i, f_i, o_i, h_i, y_i

Start Process: indicate the inputs with effective weights

- *Define all the formulative functionalities for Layers and loss estimation using filter types and optimization algorithms.*
- *Input layer: Maximum length of query: Queries for users*
- *Embedding layer: Vocabulary size: Can be varied from 100-1000 depending upon the maximum length of the query.*
- *Indicate the overall input shape and its properties to each layer*
- *Check for redundancy of the layer connectivity with values in filter size.*
- *Finally, a collective model for the both encoder and decoder structure indicating the overall design model.*

For i = 1:N

For j =1:K

$$In_i = S(W_i * (h_{i-1} + b_i))$$

$f_i = S\left(W_f * \left(h_{i-1} + b_f\right)\right)$
$o_i = S(w_i(c_i, h_{i-1}, x_i + b_o))$
$c_i = f_i * c_{i-1} + i_i * \left(\tanh\left(W_{cf} * h_{i-1}\ \right)\right)$
$h_i = o_i * \tanh\ (c_i)$
$end\ Loops$
End Process
End algorithm

Formulations:
The overall estimation of the proposed model is calculated based on the effective probabilities observed when applying the overall layers to the model. We know that $metrics\ \propto loss$, hence the estimated loss for a layer is calculated based on the equations (1) and (2) as mentioned in the algorithm representing using Conditional expected probability:

$$P\left(\frac{x_i}{y_i}\right) = p(y_i \cap x_i) * \frac{p(y_i)}{p(x_i)} \tag{3}$$

The estimated layer equation for the proposed algorithm is given by:

$$X_{fc} = \sum_{j=1}^{N} X_{cm} * w_{n+1} + X_{mp} * H(k) \tag{4}$$

$$E(X \cap M) = E\left(X_{fc}\right) + e^{E(M)} \tag{5}$$

Similarly for Y we have,

$$E(Y \cap T) = E(Y) + e^{E(T)} \tag{5}$$

The final equation for which the estimated loss is calculated based on the linear interpolated approach is:

$$\nabla\left(\frac{X}{Y}\right) = \frac{\nabla\left(E(X) * \frac{E(X\cap T)}{E(Y)}\right)}{\nabla\left(X_{fc}\right)} - E(Y) * \frac{\frac{E(Y\cap T)}{E(X)}}{\nabla(X_a)} \tag{6}$$

Hence with the formulation of the del(operations) as the partial derivates of the layer formulated obtains the overall loss estimated based on the equation (6).

IV. RESULTS AND DISCUSSION

The overall implementation of the design with LSTM and CNN indicating the different modelling approached to realize how the embedding of the data and its features of the user -bot responses are generated based on the model classification accuracy and loss. The proposed work with LSTM approach have been realized to provide such changes in the plotting of the different responses with user and bot cases. These graphs relate effective features generated using Tokenizing the texts based on the different functional changes as mentioned below:

- Dataset Acquire
- Data creations
- Data Tokenization
- Data Conversions
- Model Creation
- Chatbot representation.

1. DATA ACQUIRE

```
{'intents': [{'tag': 'greeting',
   'patterns': ['Hi there',
    'How are you',
    'Is anyone there?',
    'Hey',
    'Hola',
    'Hello',
    'Good day'],
   'responses': ['Hello, thanks for asking',
    'Good to see you again',
    'Hi there, how can I help?'],
   'context': ['']},
  {'tag': 'goodbye',
   'patterns': ['Bye',
    'See you later',
    'Goodbye',
    'Nice chatting to you, bye',
    'Till next time'],
   'responses': ['See you!', 'Have a nice day', 'Bye! Come back again soon.'],
```

Figure 5: Representing the overall dataset for Chat bot

The first step is to Acquire the data from the real time data from the user inputs from JSON file indicates the training and testing samples for the design. Each of the samples are pre-processed to create a custom formatted data features with intents based on the tags with real time user responses-based chat corpus added.

2. DATA PREPROCESSING

```
data
```

	inputs	tags
0	Hi there	greeting
1	How are you	greeting
2	Is anyone there?	greeting
3	Hey	greeting
4	Hola	greeting
5	Hello	greeting
6	Good day	greeting
7	Bye	goodbye
8	See you later	goodbye
9	Goodbye	goodbye
10	Nice chatting to you, bye	goodbye
11	Till next time	goodbye
12	Thanks	thanks
13	Thank you	thanks
14	That's helpful	thanks
15	Awesome, thanks	thanks
16	Thanks for helping me	thanks
17	Can I transfer my Current Account from one bra...	accounts

Figure 6: Representing the overall dataset for Chat bot in data-table format

In the data creations feature, we improvise such removal of unnecessary text related to the classification indicating the punctuations and other features of special characters.

3. DATA TOKENIZING

Tokenizing and Padding

```
tokenizer = Tokenizer(num_words = 20000)
```

```
tokenizer.fit_on_texts(data["inputs"])
```

```
train = tokenizer.texts_to_sequences(data["inputs"])
```

```
train
```

```
[[47, 24],
 [2, 25, 3],
 [4, 48, 24],
 [49],
 [50],
 [51],
 [52, 53],
 [26],
 [54, 3, 55],
 [56],
 [57, 58, 1, 3, 26],
 [59, 60, 27],
 [12],
 [61, 3],
 [62, 28],
 [63, 12],
 [12, 5, 64, 16],
 [8, 9, 17, 29, 65, 13, 18, 19, 30, 1, 20],
 [2, 1, 17, 13, 18, 19, 30, 1, 20],
 [4, 66, 67, 21, 68, 69],
```

Figure 7: Representing the tokenizing operation using Tokenizer function

In the third step use the custom functionality of tokenizing the words and its features based on the ascii format. For each letter and word specific numerical values are observed.

4. MODELS IMPLEMENTATION

INCEPTION-LSTM:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 15, 10)            1230

 lstm (LSTM)                 (None, 15, 150)           96600

 conv1d (Conv1D)             (None, 14, 1024)          308224

 conv1d_1 (Conv1D)           (None, 13, 512)           1049088

 conv1d_2 (Conv1D)           (None, 12, 256)           262400

 conv1d_3 (Conv1D)           (None, 11, 256)           131328

 conv1d_4 (Conv1D)           (None, 10, 256)           131328

 bidirectional (Bidirectiona  (None, 10, 300)          488400
 l)

 flatten (Flatten)           (None, 3000)              0

 dense (Dense)               (None, 2000)              6002000

 dense_1 (Dense)             (None, 21)                42021

=================================================================
Total params: 8,512,619
Trainable params: 8,512,619
Non-trainable params: 0
```

Figure 8: Representing the overall summary of parameter and layers utilized in the design

In the fourth step, we have observed with different response and conversation of the text are collaborated with numerical value indicating the specific encoding feature based on the type of the responses form the user or bot. Finally, the last case is to create and predict the model based on the real time user bot responses. We create such feature on training and testing samples of 20% size indicating the overall perspective in performance characteristics of the design.

IMPLEMENTED RESULTS WITH LSTM-INCEPTION-CNN:

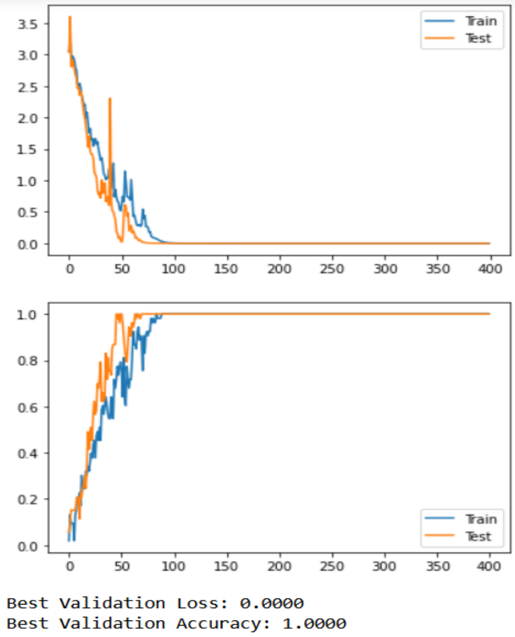
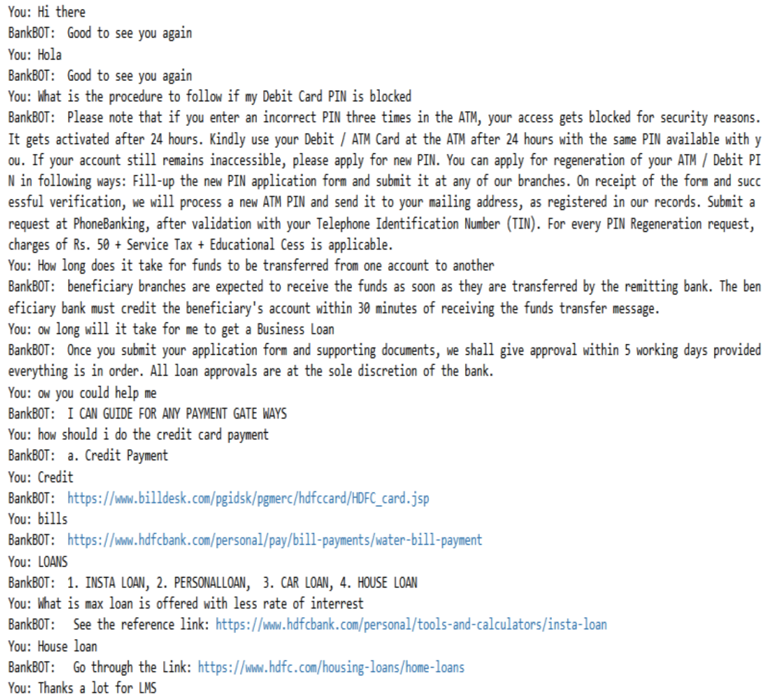


Figure 9: Representing the overall training and testing accuracy for the Hybrid LSTM-CNN approach



You: Hi there
BankBOT: Good to see you again
You: Hola
BankBOT: Good to see you again
You: What is the procedure to follow if my Debit Card PIN is blocked
BankBOT: Please note that if you enter an incorrect PIN three times in the ATM, your access gets blocked for security reasons. It gets activated after 24 hours. Kindly use your Debit / ATM Card at the ATM after 24 hours with the same PIN available with you. If your account still remains inaccessible, please apply for new PIN. You can apply for regeneration of your ATM / Debit PIN in following ways: Fill-up the new PIN application form and submit it at any of our branches. On receipt of the form and successful verification, we will process a new ATM PIN and send it to your mailing address, as registered in our records. Submit a request at PhoneBanking, after validation with your Telephone Identification Number (TIN). For every PIN Regeneration request, charges of Rs. 50 + Service Tax + Educational Cess is applicable.
You: How long does it take for funds to be transferred from one account to another
BankBOT: beneficiary branches are expected to receive the funds as soon as they are transferred by the remitting bank. The beneficiary bank must credit the beneficiary's account within 30 minutes of receiving the funds transfer message.
You: ow long will it take for me to get a Business Loan
BankBOT: Once you submit your application form and supporting documents, we shall give approval within 5 working days provided everything is in order. All loan approvals are at the sole discretion of the bank.
You: ow you could help me
BankBOT: I CAN GUIDE FOR ANY PAYMENT GATE WAYS
You: how should i do the credit card payment
BankBOT: a. Credit Payment
You: Credit
BankBOT: https://www.billdesk.com/pgidsk/pgmerc/hdfccard/HDFC_card.jsp
You: bills
BankBOT: https://www.hdfcbank.com/personal/pay/bill-payments/water-bill-payment
You: LOANS
BankBOT: 1. INSTA LOAN, 2. PERSONALLOAN, 3. CAR LOAN, 4. HOUSE LOAN
You: What is max loan is offered with less rate of interrest
BankBOT: See the reference link: https://www.hdfcbank.com/personal/tools-and-calculators/insta-loan
You: House loan
BankBOT: Go through the Link: https://www.hdfc.com/housing-loans/home-loans
You: Thanks a lot for LMS

Figure 10: Representing the overall bot Results for the design using LSTM+CNN Hybrid model

The figure 9-10 represents the overall training and testing cases for 400 epochs of iteration based on the parameter setting using Hybrid LSTM+CNN approach as improvised with the data. While in Figure 10 shows the overall design results with chat response with user and bot requests as per the query. We have observed all test cases are true when effected with parameter testing on the prediction of banking bot responses for the proposed model design. The table-1 displays the overall performance of the design approach indicating the performance factors as accuracy, F1-score, sensitivity and specificity.

Table 1: Representing the overall Comparison Results for the existing and Proposed model

METRIC	EXISITING	PROPOSED
ACCURACY	99.4	100
F1-SCORE	96.56	99.86
SENSTIVITY	98.45	99.56
SPECIFICITY	97.32	99.63

V. CONCLUSIONS

The overall design with LSTM has proven best results with loss less than 1% and average accuracy of 100% from the results section V. The chat response for the overall design indicating one of the aspects to realize the model accurate behaviour indicate the any changes in the dataset or even custom dataset wouldn't change the design outcomes as predicted.

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