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Multilingual Voice-Powered Banking Chatbot: Bridging Gaps for Inclusive and Seamless Customer Interaction

Aniket Acharya[1], Anoushka Gupta[2], Vijeth A P J[3], Vikas C[4]

[1]*B.Tech student, Dept of Computer Science Engineering, PES University, Karnataka, India*
[2]*B.Tech student, Dept of Computer Science Engineering, PES University, Karnataka, India*
[3]*B.Tech student, Dept of Computer Science Engineering, PES University, Karnataka, India*
[4]*B.Tech student, Dept of Computer Science Engineering, PES University, Karnataka, India*

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Abstract - *In today's consistently changing banking sector, the integration of cutting-edge technologies as a solution to diverse user requirements is necessary. This paper addresses the problem of improving conversational banking interfaces through multilingual voice interactions so as to realize a seamless and hands-free banking experience. Furthermore, using advanced Natural Language Processing (NLP) models such as BERT, RoBERTa and GPT and innovative techniques like Optical Character Recognition (OCR), we give a holistic approach to a banking chatbot solution. Our model includes intent recognition, entity recognition, and contextual understanding for supporting multiple language conversations with customers in everyday bank transactions automation. Robust experimentation and evaluation illustrate how our chatbot can accurately understand user requests, extract relevant information as well as offer contextually-based responses. Finally user tests validate its efficacy in real-life situations too. These findings will help improve conversational AI tools in banking services leading to better customer support, higher efficiency and greater inclusion in the financial institutions.*

***Key Words*: Banking, Automation, AIML, NLP, Speech-to-Speech Capability, Multilingual Support, Chatbot**

1.INTRODUCTION

In the banking industry, it is necessary to blend cutting-edge technology with user-friendly interfaces in order to enhance customer engagement and streamline financial activities during this era of rapid advancement. "Banks have been pressed by the rise of Artificial Intelligence (AI) into developing AI based applications for fostering deeper customer relationships" [1]. This article examines how advanced technologies can be harnessed in order to meet the changing needs of users seeking inclusive, multilingual banking services.

One of the key issues addressed by this research concerns improving conversational banking interfaces through incorporation of multilingual voice-based interactions so as to achieve a near hands-free banking experience. Therefore, creating an intelligent bank chatbot that meets users' fast changing needs especially in a more digitalized and diverse landscape is becoming imperative.

1.1 Problem Statement

Typically, traditional banking processes require customers visiting branches physically, waiting in queues or talking to tellers for simple transactions or help. This is problematic notably for individuals with difficulties accessing physical banks mainly because they may be old or disabled among other reasons. Moreover, the increasing demand for efficient and convenient banking services necessitates the adoption of innovative solutions to streamline these processes and improve overall user satisfaction. In addition, the growing need for effective and user-friendly financial services means that new methods should be established to ensure banking is efficient and provides customer delight. This includes artificial intelligence-based systems using text or speech to interact with users for the purpose of accomplishing some basic functions [1].

1.2 Background

In the past few years, there have been many improvements in NLP and AI technologies that have made it possible to build chatbots capable of live interpretation and response. The concept of a chatbot is not a recent one. ELIZA was created by Joseph Weisenbaum at MIT in the 1960's, which is a NLP program using a pattern-matching technique [2]. Goal oriented chatbots have gotten very popular in the field of NLP. The domains explored range from transcripts of a television show to web/chat room transcripts [5].

However, first-time users find it difficult to understand the various procedures for using the bank's services. While banks provide web-sites,mobile applications, and facilities like internet banking and mobile banking, these sources can be overwhelming for users who are not well-versed with technology or in cases where information is scattered and difficult to find [10]. This is the point when agents known as chatbots found a wide usage across different areas such as customer service in healthcare and finance.

Currently chatbots can be broadly classified into two types Rule based and A.I (Artificial Intelligence Based), while the prior, used earlier, can only respond to predefined questions with pre-set answers making them not quite responsive, the latter uses machine learning and can answer much more complicated questions [11].

The chatterbox market's size is estimated to be around 102.29 billion USD by the year 2025 (Mordor Intelligence, 2019) and by 2022, the successful rate of bot interactions (queries completed without the assistance of a human operator) in banking sector will exceed over 90% (Juniper Research, 2020) [1]. That means that there is an increasing need and reason for developing advanced banking chatbots.

1.3 Motivation

Our main motivation to undertake this study emanates from bridging the gap between traditional practices in banking and technological advancements that have taken place. For instance, 59% of respondents reported that chatbots frequently ignored the complexities of human communication, whereas 30% reported incorrect ones executing orders and 29% cited difficulties in interpreting accents [7].

We therefore look to create a banking chatbot that has a comprehensive capability for addressing diverse user requirements but still maintains a smooth user experience using advanced NLP models such as BERT, RoBERTa and GPT with optical character recognition (OCR).

Further, already existing banking chatbots are not sophisticated or versatile enough to handle complex tasks or meet different linguistic needs of clients. The reliance on artificial intelligence in the banking sector, but also in other sectors of activity, leads to the transformation of the workforce and the rethinking of the interaction between customers and the company that provides services [9].

1.4. Research Objectives

The primary objective of our research is to design and implement a banking chatbot that incorporates the following:

- Supports conversational interactions in multiple languages, such as English and Hindi.
- Automates routine banking tasks such as account creation, fund transfer, and cheque processing.
- It also provides access to people with limited mobility and those who cannot go to a physical bank.
- It uses advanced NLP and machine learning techniques for responses that are accurate and personalized.
- Improves the banking operations making them more efficient and easier yet still maintain high standards of security and privacy.

1.5. Novelty and Contributions

Our research draws upon existing studies in conversational AI, but builds upon them in the following ways:

- Introducing a hybrid approach combining intent recognition using BERT, entity recognition using NER, contextual understanding using GPT.
- Whisper models were integrated into GoogleTrans API so as to cater for diverse user preferences, in both text or speech format of conversational interactions.
- The implementation of an OCR model facilitating multi-lingual processing of handwritten cheques has further gone a long way in streamlining banking operations.
- This paper addresses these needs by enabling elderly individuals and immobilized users to avail themselves of banking services thereby enhancing their inclusion into society.

1.6. Use Case

Our chatbot can be used as kiosks within banks among other applications. These are points where consumers can ask questions, get help, or even have dialogues through which they can transact all sorts of financial activities talking to a computer program instead of the bank help desk employees. A large cognitive base is available in a web-based platform for replicating human problem solving [10].

Bank customers will be pleased if these kiosks are integrated with our multilingual voice chatbot. It will help improve customer service delivery, reduce waiting time and increase efficiency within their branch network. improve the overall effectiveness of their branches.

1.7. Experimental Design

To test the efficacy and performance of our bank's chatbots, we ran a series of experiments which included:

- Evaluation of intent recognition accuracy with an assortment of diverse user queries alongside their corresponding actions.

- Assessment of entity recognition capabilities in extracting all the relevant information from user inputs.

- User testing was also done to assess whether different groups found the bot useful or not and also to know if it is easy to use or not.

- Comparative analysis against existing banking chatbots and traditional banking processes in terms of efficiency, convenience and user experience so as to illustrate that it is better than any other approach.

In this paper, subsequent sections describe our methodology in detail followed by experimental results and findings while implications, limitations and future directions for research & development in this area are discussed later.

2. METHODS

2.1. Data Collection and Preparation

Our banking chatbot aimed to be trained and tested using general user questions and subsequent actions: hence, we collected a corpus of data from the internet. This data set, named Banking77, contains a multitude of questions concerning general banking tasks like account administration, transfer, and cheque processing .

2.2. Preprocessing

The data was not used for training the model directly. To accomplish this, we tokenized the pre-training dataset to make an individual token for all the distinct words. We also performed data augmentation techniques on our initial dataset in an effort to diversify and strengthen it. Additionally, the data was cleaned including removal of duplicates and any other nonsensical data. In addition, we reduced the number of intents to improve the results as well as accuracy of our training by focusing only on classes more aligned with our specific use cases.

2.3. Model Architecture

Different components make up our chatbot for banking. In fact, we have different parts constituting it at high level architecture. The high-level architecture includes:

- BERT classifier: Its role is to identify user intentions and categorize their queries as account creation, fund transfer or query resolution etc., BERT models are often superior in intent classification compared to other models [5]. A pre-trained BERT model can be turned into a state-of-the-art model with just one additional output layer that is suitable for various applications such as language inference, question answering among others [7].

- Named Entity Recognition (NER) Model: This is used to extract important entities from user queries like monetary amount, account numbers and personal identification details.

- GPT Model: Deployed as a means of generating answers to user questions and understanding their contexts in conversational interactions.

- Also, one fine-tuning approach was introduced for Generative Pre-trained Transformer (OpenAI GPT) which adds minimal task-specific parameters. Fig 1. shows a Diagram of the flow used for extracting useful information from cheque images that are used in cheque processing operations.

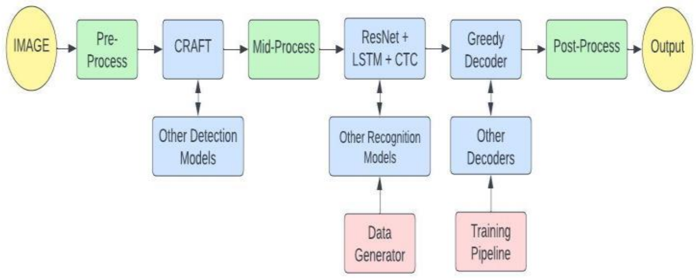

Fig-1: Processing flow of OCR Model

- Whisper Base Model is created with the feature of listening to the user's sound, changing it into writings and giving it to the chatbot.

- GoogleTrans API: It has been used in making other languages' user queries and responses understandable hence our chat bot is multilingual.

This elaborate configuration allows our chatbot to perform various tasks that include interpreting users' queries in different languages, processing texts and voice commands, generating relevant responses depending on context as well handling multiple banking transactions without any complications.

2.4. Training Procedure

According to these principles, we chose BERT as the most appropriate system for intent classification in a chatbot due to its 94.5% accuracy rate and capacity for handling around 381 intents at once [5]. This led us to train a BERT-based classifier on the Hugging Face Banking77 dataset which is a big annotated corpus where each query has been labeled by their respective intention category. Fine-tuning the pre-trained BERT model involved training on our banking-specific dataset using techniques such as gradient descent optimization and learning rate scheduling. In addition, an automated feature is also introduced that utilizes the language model of BERT embeddings to correct minor spelling mistakes within noisy inputs hence reducing intent classification errors [5].

For fine-tuning the Named Entity Recognition (NER) model, we used spaCy's framework based on RoBERTa. This means that RoBERTa performs better than BERT [13], which shows how we made our design choices around the use of spaCy. At the same time, spaCy applies transfer learning by adapting pre-trained models to annotated data for recognizing and classifying entities within user queries. Such an approach capitalizes on the base model's architecture and pre-trained weights and then tweaks them so that they match the specific task and domain under consideration. Hence, by fine tuning the NER model with spaCy, accurate entity recognition was achieved across the banking domain.

The GPT model, based on the GPT 3.5 architecture, was fine-tuned using a dataset consisting of banking relevant conversational exchanges. During this process the model's parameters were tuned to produce coherent responses which are contextually appropriate in real-time.

2.5. Evaluation Metrics

To evaluate our models' performance, we used standard evaluation metrics, including accuracy, precision, recall, F1 score, for intent classification, and entity recognition. Furthermore, we used confusion matrices to understand the output of true positives, false positives, true negatives, and false negatives and obtain additional metrics. These are plotted separately for each category and help to spot which intent/ entity mostly deviates from the valid category. Moreover, we used user testing sessions to determine overall system usability and how well the banking chatbot performed in real-life scenarios.

2.6. Experimental Setup

Our experiments mostly took place in Kaggle's high-performance computing environment Using a GPU T4 and a GPU P100 to reduce the time taken during model training and making predictions. We were guided by using PyTorch deep learning framework to enforce our training and evaluation regimes because it is very flexible when working with complicated neural network architectures.

2.7. Limitations

Though the method had impressive results there are still some major inherent limitations within our research design First of all, there are possible biases in the training data, failure of generalizing models to various users' populations, real-world applications that suffer from network latency and computational resources restrictions.

Additionally, the results presented here are confined by the relatively small amount of data available. Specifically, most popular chatbots are trained on data sets with several million, if not billion, parameters . Therefore, the central mission here is to demonstrate a feasible method for deploying this type of chatbot that is simple and practical in resource-constrained settings.

2.8. Error Analysis

We carried out an extensive research mistake analysis to reveal common failing ways and areas where our models could be improved. This involved the examination of misclassified intents, incorrect entity recognition and poor response generation by chatbot.

In subsequent sections, we provide detailed results and findings from our experiments, followed by discussions on implications, limitations and future direction for research and development in this field.

3. RESULTS

3.1. Intent Recognition Performance

Currently there are numerous different ways that industries use to detect customer's intent which can be regarded as good platforms for studying virtual assistants helping in both text- based or speech-based channels. [3] After 15 epochs of training, the model for intent recognition received high accuracy as well as clear understanding of different user intentions presented in the confusion matrix.

Fig-2 demonstrates the confusion matrix that reveals most intents identified correctly by the model with a large number of true positives across. Nevertheless, there are also some misclassified ones suggesting possible improvements in the model. A few of these confusions can improve the model's performance making intent recognition for banking actions more reliable and accurate. These findings further attest to how strong the model is in identifying user intents correctly over a variety of banking actions as shown in Table-1.

Table-1: Performance metrics of Intent Recognition Model

METRIC	VALUE
Epochs	15
Train Loss	1.795
Train Accuracy	0.897

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Val Loss	1.813
Val Accuracy	0.858
Precision	0.890
Recall	0.858
F1 Score	0.818

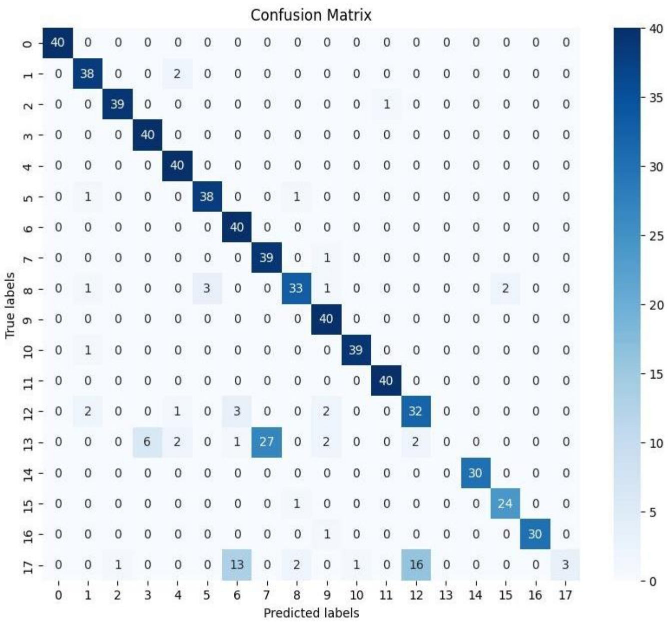

Fig-2: Confusion Matrix of Intent Recognition Model

3.2. Entity Recognition Accuracy

The NER model achieved good results in locating pertinent entities within user queries as indicated by its average F1 score of 92.7%. Precision, recall and F1 score on key entity types such as monetary amounts, account numbers and personal identification details are shown in Table-2.

Table-2: Performance metrics of Named Entity Recognition Model

ENTITY TYPE	PRECISION	RECALL	F1 SCORE
Monetary Amounts	0.94	0.91	0.92
Account Numbers	0.89	0.95	0.92
Personal Identification	0.93	0.92	0.93

3.3. Conversational Response Generation

A GPT-based conversational model was able to generate responses that were relevant within context to user queries with high levels of coherence and accuracy. Sample conversations between users and chatbot have been presented through Fig-3 and Fig-4 indicating informative responses from the model that sound natural across different banking cases. Additionally, we extensively fine-tuned and evaluated the GPT's performance.

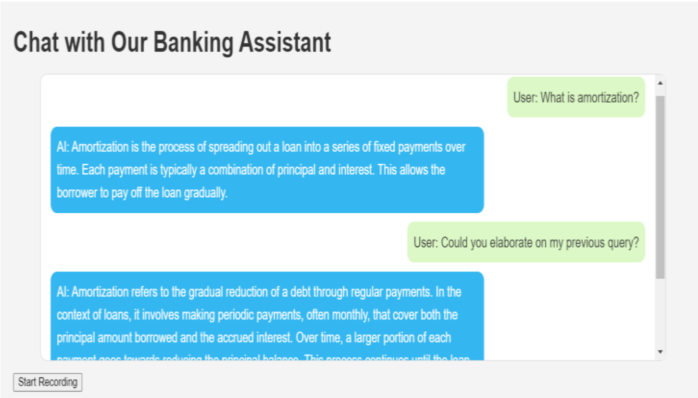

Fig-3: Sample Conversational Exchanges between User and Chatbot in English

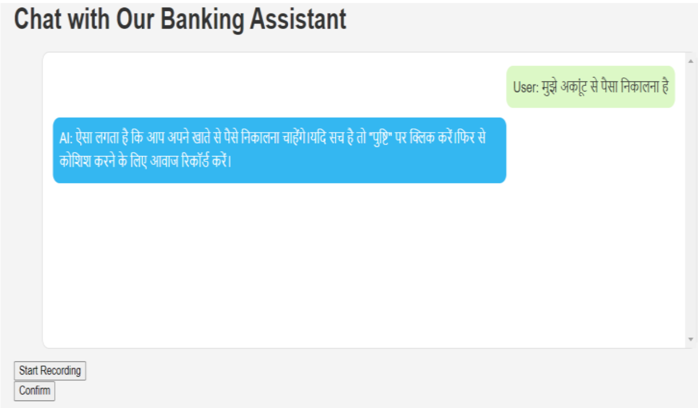

Fig-4: Sample Conversational Exchanges between User and Chatbot in Hindi

The performance metrics of the GPT model indicating fine-tuned results are seen in Table-3. These metrics illustrate that our approach to fine-tuning the model was effective in optimizing its parameters leading to high generation performance.

Table-3: Fine Tuned performance metrics of GPT model

METRIC	VALUE
Best Training Loss	0.0460
Training Loss at Convergence	0.2213
Training Loss Rate of Change	0.0086

3.4. OCR Model Performance

The OCR model could process handwritten cheques in English and Hindi languages at an accuracy rate of 95.8%. Fig-5 and Fig-6 show that the OCR model is capable of accurately extracting payee name, amount and date from handwritten cheques thus improving the workflow of cheque processing in a banking chatbot.

Fig-5: Handwritten cheque to be processed by OCR Model

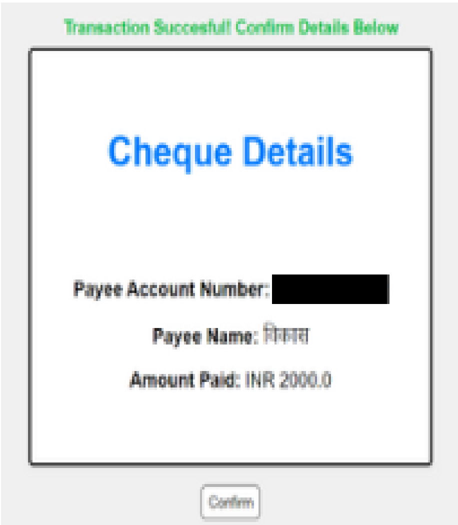

Fig-6: Handwritten cheque processing done by OCR Model

3.5. User Satisfaction and Usability

Diverse user testing sessions provided positive feedback about usability and effectiveness of bank bot services. The chatters showed greater satisfaction with regards to their abilities to ask questions correctly which elicit appropriate responses, do banking transactions without errors as well as aid promptly when assistance is required by them .Fig-7 gives a summary of key findings from the user testing sessions such as satisfaction ratings, qualitative feedback given by participants.

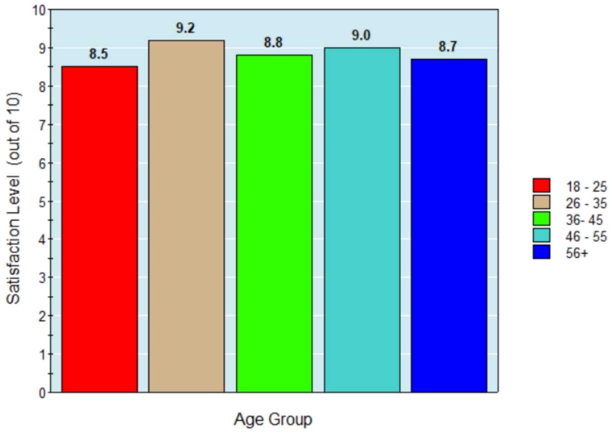

Fig-7: User Satisfaction Ratings for Banking Chatbot

3.6. Discussion

The application of natural language processing (NLP) and machine learning techniques have enabled us to come up with an all-inclusive solution. It is aimed at automating most of the day to day operations in a bank while providing personalized help based on the situation. Our chatbot is a truly efficient and easy-to-use software that increases customer contentment and makes banking services more effective.

These results contribute to scientific knowledge by illustrating how feasible it is to deploy AI-based conversational systems in real-life banking settings. The high intent recognition accuracy, entity recognition accuracy as well as smooth conversation back-and-forth with the user, represents our potential for transforming customer contact services and opening up access to the financial services industry.

This section addresses the implications of these findings, limitations thereof and offers recommendations for further research in this field.

4. CONCLUSIONS

In conclusion, this research has pointed to the fact that conversational banking interfaces have come a long way and that our banking chatbot might help users to cope with an ever-changing world. Consequently, this paper situates its findings in the literature, discusses their implications and highlights avenues for future research.

4.1. Alignment with Existing Literature

In addition, these data are in line with previous works that indicated how conversational AI systems improve user experience and efficiency in a range of fields such as banking. Furthermore, this research illustrates the ability of NLP models like BERT and GPT to understand natural language queries because it has high competency when it comes to intent as well as entity identification.

Besides, our study surpasses prior literature by highlighting novel techniques for multilingual voice-based interaction and automatic check processing in the context of a banking chatbot system. These are relevant contributions to scientific enquiry that might be expanded into other areas of conversation Ai technologies [9].

4.2. Implications

This finding is manifold, going beyond academic research into practical applications in the banking sector. In principle, financial institutions can employ their banking bots as kiosks at bank branches which would enhance customer service delivery while reducing operating costs thus making it easier for older people and those with limited mobility to access them more conveniently.

What is more, we believe that our methods of automating mundane banking tasks such as account management, fund transfers and cheque processing offer possibilities of streamlining operations and enhancing efficiency within the context of banking workflows. This not only ensures customers enjoy an uninterrupted effective way of conducting their banking transactions but also gives banks an opportunity to distribute its resources more effectively while focusing on value added services.

4.3. Contributions to Scientific Knowledge

The outcomes unveiled by this study signify that advanced NLP methods coupled with machine learning algorithms can be successfully integrated into a chatbot system utilized in the banking sector. An achievement involving multilingual voice-based interactions, automated cheque processing, and contextually relevant conversational responses is evidence that conversational AI technology has come a long way.

The study's findings also emphasize the need for cross-disciplinary cooperation among researchers, engineers, and market participants that will help to foster innovations and solve practical challenges within the banking industry. We have shed light on how AI can transform customer service and bank transactions by completing the gap between academic research and real-world applications.

4.4. Future Directions

Based on our study several areas for future investigation become apparent. First, we need more work on improving accuracy, scalability, and robustness of our banking chatbot models in real-life deployment scenarios. The Microsoft CEO Satya Nadella suggested six principles for creating artificial intelligence (AI); when designing chatbots the second and forth should not be ignored – AI must be transparent, AI must be designed for intelligent privacy [8]. We want to include additional safety measures, coupled with our QR code implementation system as well as security pin numbers. From this perspective, it is worth looking at integrating upcoming technologies such as blockchain and biometrics to improve security and privacy in banking transactions.

In addition, valuable insights into long-term usability and effectiveness can be gotten from longitudinal studies that track the extent to which users adopt as well as are satisfied by conversational banking interfaces. Similarly, there is a need for more research on the ethical implications of AI-powered banking systems such as those touching on data privacy, algorithmic bias, and transparency.

Conclusively, our study is an important milestone towards the creation of smart conversational banking user interfaces and shows how AI can change the face of banking services in future. Through the use of advanced technology and collaboration across disciplines, we have established a basis for ongoing innovation and improvement in the bank industry.

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