CHAT-BOT SYSTEM FOR COMPUTERS, ACCESSORIES & REPAIR CENTER RECOMMENDATION

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Shanila Udaraka Thirimanne

B.Sc. (Hons) Degree in Information technology
Specialized in Data Science

Department of Information Technology

Sri Lanka Institute of Information Technology
Sri Lanka

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Declaration

"I declare that this is our own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant to Sri Lanka Institute of Information Technology, the nonexclusive right to reproduce and distribute my dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books)."

Name	**Student ID**	**Signature**
Thirimanne S.U.s	IT2022506	

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Dr. Lakmini Abeywardhana Date
(Signature of the Supervisor)

Acknowledgement

We would like to express my heartiest gratitude to all who have contributed in the development in this proposal document. First and foremost, we would like to express my sincere gratitude towards our research supervisor Dr. Lakmini Abeywardhana who guided us in the right path towards success of this project. We also want to express my gratitude towards the members of my team for their commitment and the support given during this project. In addition, we express our gratitude towards the people who involved in the process and gave us information we needed. Finally, we would like to express my appreciation towards our management for giving us tools and opportunity we needed to complete this project. Their steadfast assistance and dedication have been essential in assuring.

Abstract

As we live in this fast-moving digitized world, having electronic devices has become a must in life. In such, it must to have the most suitable devices to cater to your needs. Hence, in traditional days we tend to ask for such help or search for devices in all possible ways. Thus, it is best if we could have all in one place for us to identify the best device we need upon the requirement. Hence, my team and I have proposed a Chat-Bot recommendation system for computers, accessories and repair centers. Thus, our title of this research project; "Chat-Bot System for Computers, Accessories & Repair Center Recommendation"

As we identified Chat-Bot system is the most novel approach for this. This system uses Natural Language Processing techniques to understand the user's preferences and give them the optimum results. Furthermore, Chat-Bot systems are more likely to be lively in this fast-digitizing world. This abstract provides an overview of the Chat-Bot recommendation system, which is an innovative and user-friendly way to assist users in selecting the best solutions.

Thus, we are looking forward to give the best solutions towards users by collecting reviews of devices and repair centers. We are looking forward in web-scraping certain websites to gather our relevant data as well. In addition, we are introducing image processing in order to identify computer accessories without any difficulties All these features will be available through our Chat-Bot system such that any personnel with varying knowledge of electronic devices can get a solution without any hesitation.

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Table 1 - List of Abbreviations

Abbreviation	**Meaning**
NLP	Natural Language Processing
NER	Name Entity Recognition
PC	Personal Computer
ML	Machine Learning

1. Introduction

The development of technology and e-commerce platforms has made it simple for people to buy for a variety of goods online. For many people, however, it can still be difficult to locate the perfect product. The battle can be broken down into other categories, such as determining the product's requirements and purpose, taking financial limits into account, and judging the product's durability. Because of their interdependence, choices made in one area may have an impact another.

Thus, enters Chat-Bot systems. Which helps users to feel more alive & a platform to suit their needs at its best. A chatbot system is made to mimic human communication and help users find the right items to meet their needs. With the development of technology, chatbots have gained popularity. Chatbots can offer relevant items and reduce shopping challenges by learning about customer preferences and requirements. The chatbot serves as an informed advisor, making suggestions based on criteria including purpose, price, and durability. Chatbots can assist users in making better educated judgments about their purchases and enhance their overall shopping experience in this way.

The very first Chat-Bot introduced to the world was “ELIZA”. From then onwards, use of chat-bots have drastically increased due to the reasons explained above. This is clearly showcase in the following diagram which is statistically proven in the research of “*A literature survey of recent advances in Chatbots*”. [1]

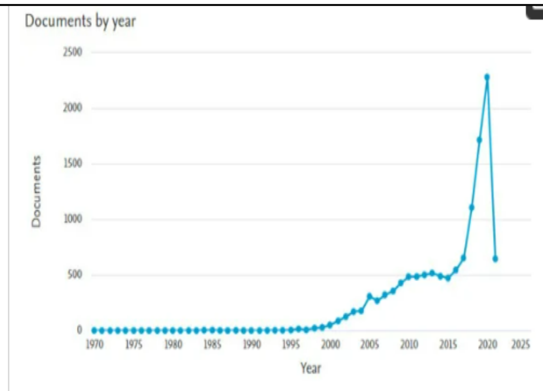


Figure 1. Search Results from Scopus, from 1970 to 2021 for the keywords "chatbot" or "conversational agents" or "conversation system".

1 - Search results of 'Chat-Bot' keyword

In this study, we will attempt to determine how well a chatbot's recommendation system works to meet user needs. We will also carefully examine any variables that may have an impact on customers' satisfaction with the chatbot system, as well as how the chatbot system can take users' daily activities to a higher level while requiring less time and effort. Last but not least, the goal of this research is to enhance the user experience and raise user satisfaction in the searching computers, computer accessories & service centers.

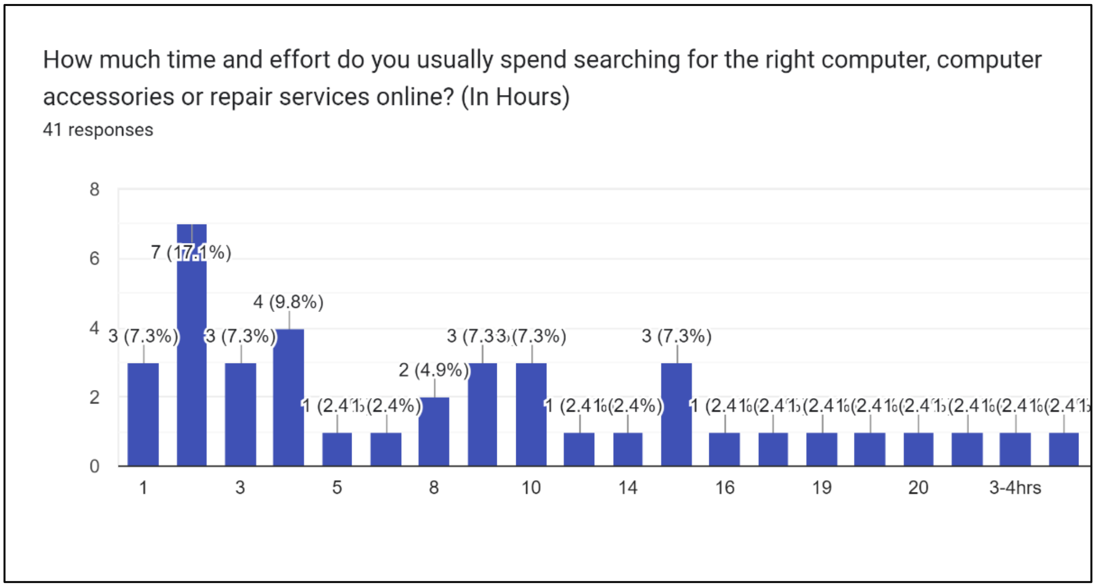
1.1 Background & Literature Survey

1.1.1 Significance of Chat – Bot for Laptop Recommendation

In order to understand the significance of this particular study, it is best to investigate the prevailing methods when an individual is searching for a device, repair center or a certain accessory. In most cases we would turn ourselves into web browsers and search for the item in need. For example, if we need to look into an device, we would search for brands, specific requirements and browse until the proper intentions are met. Since there are numerous number of brands, device specifications & customer reviews to go through, this could be a potential lengthy process. On the other hand, the next easiest option would be asking a particular technician who excels in the particular knowledge base. Thus, how useful could it be if all of these mentioned methods can be taken into account and deliver under the same roof. As introduced, this study will represent how this can be achieved.

Furthermore, many individuals struggle when identifying certain computer accessories. This could lead to certain scams when repairing their devices as well. Thus, in this study we will represent how we cater this as solution by introducing image recognition and recommending repair centers based on reviews.

In addition, upon the survey carried out it was observed that on average 10 hours has been spent searching for a new device. Thus, proving that it is a lengthy process.



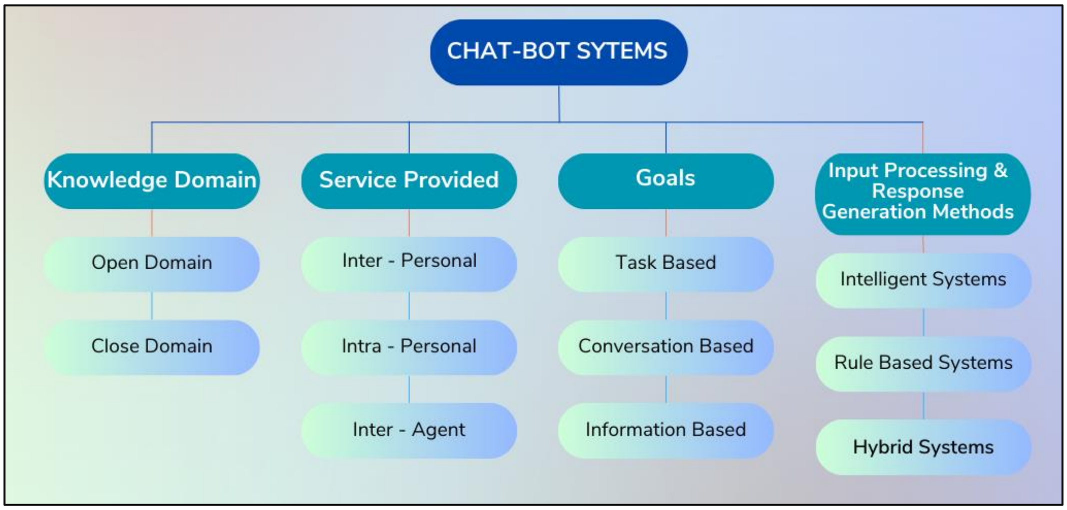
2 - Survey on Time Spent by Customers

In most cases, if we are looking forward to purchase a PC and we visit a website, there are none to rare instances of Chat-Bot systems. What we will be able to find are filtration methods. In such cases, we lose the human touch and most importantly, one who lacks device knowledge finds it hard to find a PC to cater his or her needs. Thus, its best if we could implement a Chat-Bot system to cater their needs.

In other cases, PC accessories are important as well. These can be external and internal hardware which cater many needs. This is a very useful part in which such Chat-Bot system may come in handy. Because, unlike looking for a PC/Laptop, people specifically lack knowledge in specific parts of a device. In tradition ways, we would turn over to a specialist or so. Similarly, issue stands for PC repair centers. We would browse the web or so. Hence, as in this project we opt to cater all these needs under one roof to raise user satisfaction in the searching computers, computer accessories & service centers.

1.1.2 Types of Chat - Bots

Since the significance of a chat – bot system was identified, let us now understand the types of chat – bots with the aid of the following diagram. [2]



3 - Types of Chat – Bots

As shown in the above figure, chat-bots can be categorized into several categories based on different aspects. Let us drill down to understand Chat – Bots behave and how this study represents its chat – bot.

(a) <u>Knowledge Domain</u>

a. <u>Open Domain</u>

Open Domain Chat-Bot systems have a huge variety of knowledge. It is not specified to a certain aspect. Best example for such systems is 'Alexa'. Where their domain knowledge expands into many areas.

b. <u>Close Domain</u>

Close Domain Chat-Bot systems are specified into a certain knowledge. They are train to provide a specific task in that particular area.

(b) Service Provided

a. Inter – Personal

These types of Chat-Bots provide a certain service without being a companion of the user. They just exist to provide a service to the user upon their request.

b. Intra – Personal

On the other hand Intra-Personal Chat-Bots deliberately become companions of the user and provide a service. These are much personalized to each user. ‘Alexa’ is a good example for intra-personal chat-bots.

c. Inter – Agent

These types of chat-bots are mostly used to communicate between two systems and provide a task. These are mostly automated between IOT systems.

(c) Goal Based

a. Task Based

These types of Chat-Bots accomplish a certain task such as booking a flight or so.

b. Conversational Based

As the name stands, these will mimic a conversation between the user and the chat-bot.

c. Information Based

Information based chat-bots will provide information based on the upon the user's need based on the information saved in their system.

(d) Input Processing & Response Generation Method

a. Intelligent Systems

Intelligent systems generate responses based on AI algorithms. They are capable of learning themselves to provide the best service towards the user.

b. Rule Based Systems

Rule based Systems are hardcoded within themselves. They are set to ask particular questions from the user to get the information as needed.

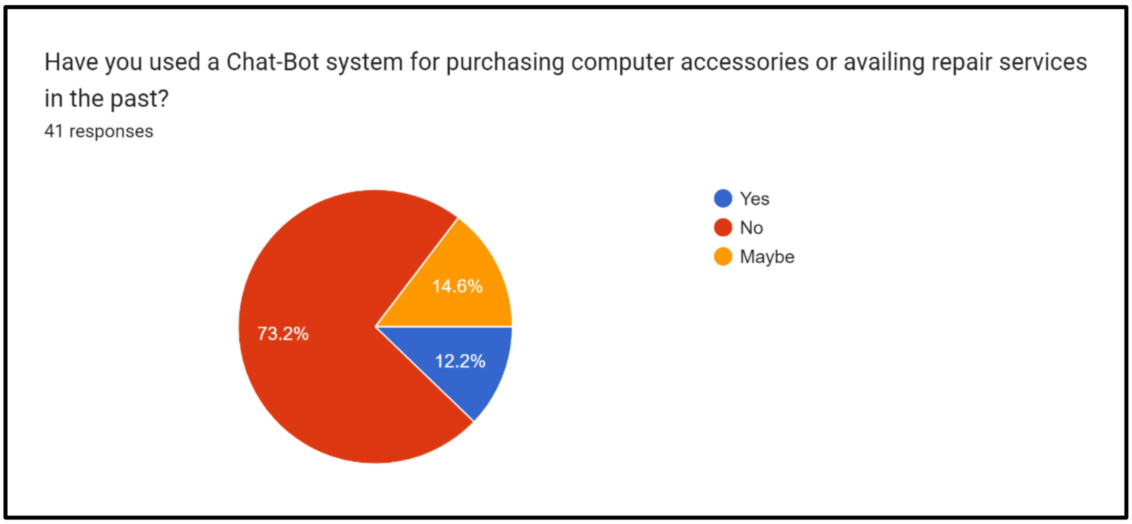
c. Hybrid Systems

Hybrid systems are a combination of Intelligent & Rule Bases systems comprising of vast capabilities.

1.2 Research Gap

In this digitized world there are numerous ways which we could represent our recommendation system. Yet, we choose a Chat – Bot based interface since it would create the most practical aspect when interacting with users and maintaining the human touch.

To secure this thought, it was observed that more than 70% users have not met such 'Chat – Bot based recommender system' via our survey as shown below.

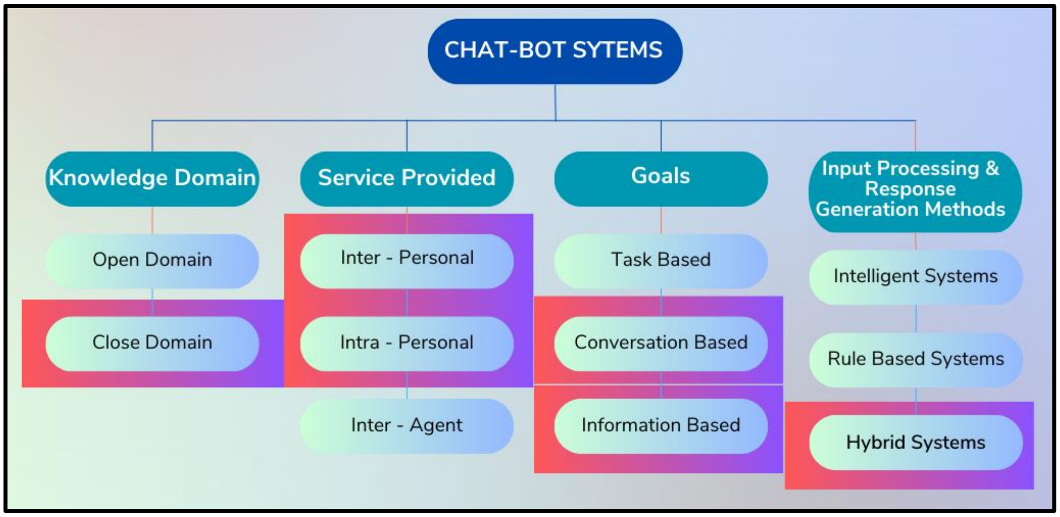


4 - Survey on Experience in Chat - Bot Related E - Commerce Systems

Looking towards already exiting chat-bots and their common drawbacks, the following were discovered.

- Limited Functionality – One of the major issues that Chat-Bot systems are facing is finding it difficult to understand multi – part questions.
- Not personalized & Lacks emotions - Most systems do not take the factor of user's emotions into account. Thus, making it difficult to give more personalized results to users.

In order to investigate how our Chat-Bot system brings novel to the users and fill the above drawbacks, let's further investigate how earlier mentioned types of Chat-Bot systems tally with our system.



5 - Types of Chat-Bot compared to proposed system

Thus, as you can see highlighted sections will cater our system. In specific, since our system caters towards recommending devices it will be a close domain system. Furthermore, in order to understand user's need we will be moving towards inter & intra personal Chat-Bot system. In such way we will be able to take the emotions of the users into account as well. In addition, in order to enhance the human touch within the system, we will develop a conversational & informational based system.

The most important of the above all is how we process the inputs and generate the responses. For this it is proposed to use a hybrid of intelligent systems and rule-based system such that we will be able to understand the user's need exactly. Thus, making this proposed system a much overall user-friendly Chat-Bot system.

In addition, the below table will elaborate on how our Chat-Bot system compares with the others and how it stands out from the others.

Table 2 - Research Gap Comparison

Research Ref. No.	**Audio Input Via Chat - Bot**	**Image Input Via Chat-Bot**	**Input & Response Generation Method**
Research [3] *Sinhala Chatbot with Recommendation System for Sri Lankan Traditional*	✗	✗	Rule based System
Research [4] *Sentiment-based Chatbot using Machine Learning for Recommendation System*	✗	✗	Intelligent based
Research [5] *A machine learning based chatbot song Recommender*	✗	✗	Rule based System
Proposed System	✓	✓	Hybrid System

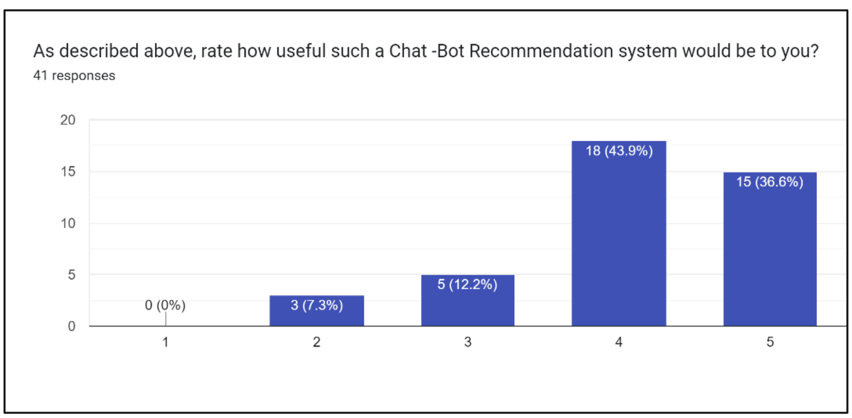
Thus, in order to develop this proposed system, the 'state – based Chat – Bot' was developed including NLP techniques such as intent classifier models and NER models which will be discussed in detail in the methodology. These techniques and technologies as us in developing the state of the art proposed Chat – Bot.

1.3 Research Problem

In this modernized world, we still lack a comprehensive, specified & reliable method to identify computers, computer accessories as per users' specific needs. We still use traditional methods such as searching on a web browser, comparing each device and so on. These are much time-consuming methods and yet sometimes unreliable due to certain circumstances. Furthermore, sometimes we struggle to find a reliable repair center near us in order repair our electronic devices such as computers. Many people still use traditional methods by getting to know through contacts or so. In such cases, they may misguide you and you'll be ending up scammed. Hence, it is best to see real world reviews of majority of people and find the most suitable repair center in order to cater your need. Even when we enter a e-commerce website, you will be needing a specific knowledge about computers or so to find you a suitable device. Thus, you will be asking guidance from someone else.

Thus, we have proposed a CHAT-BOT SYSTEM FOR COMPUTERS, ACCESSORIES & REPAIR CENTER RECOMMENDATION. In this proposed system, we try to retain the human touch as much as possible by introducing a Chat-Bot system. Which also doubles as to increase user experience and usability as well. Let's dive into the research objectives to identify specific objectives of how we will cater the optimum Chat-Bot based system to users.

In addition, it was proven positive that implementing a Chat-Bot system for recommending devices is quite useful. This can be showcase from the below diagram which was extracted from the questioner we carried out.



6 - Survey on Usefulness of Chat-Bot Recommender System

1.4 Research Objectives

The research done in this study focuses on creating a cutting-edge Chat-Bot based Recommender System in the recommender system landscape. By introducing a dynamic and interactive component, Chat-Bot based Recommender System has the potential to completely transform how users receive recommendations. The main goal of this particular component is to build a cutting-edge Chat-Bot system with the ability to recognize and respond to users' changing needs. Several essential sub-objectives that are necessary to accomplish this main objective have been identified.

The study's primary goal is to design a Chat-Bot interface that is both aesthetically pleasing and user-friendly. This factor is crucial because it not only guarantees the delivery of helpful recommendations but also improves the user experience by involving them in an interesting visual interaction.

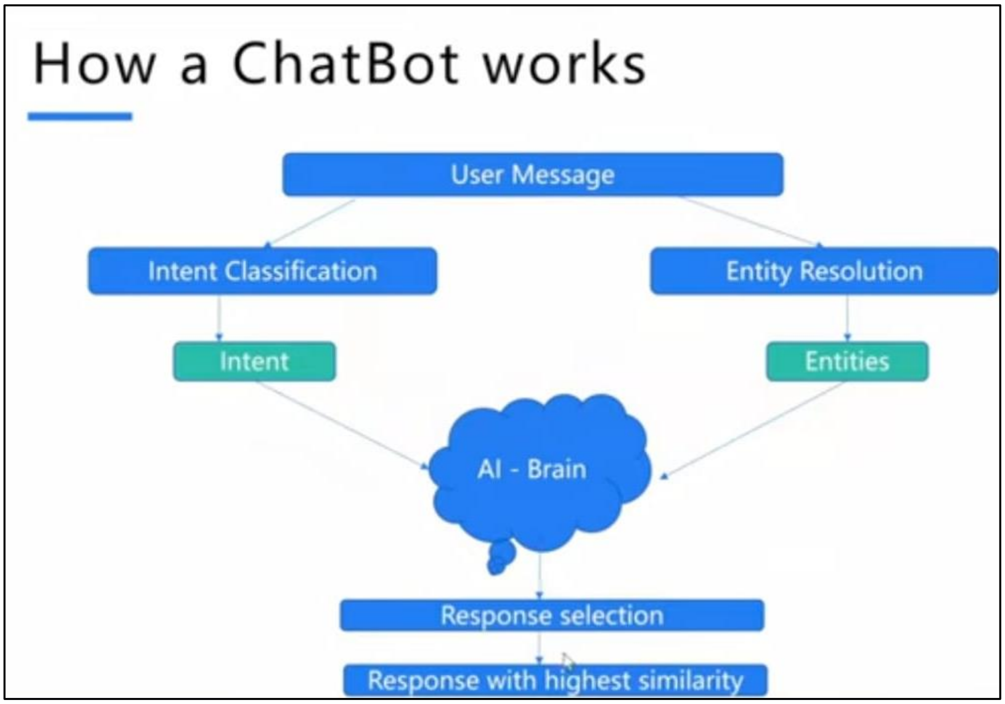
The research also works to make the chatbot's ability to accept audio and visual inputs as efficient as possible. The system's horizons are widened by this optimization, enabling a greater variety of user interactions to be processed and dealt with. The Chat-Bot based Recommender System aims to cater to a larger audience with a variety of preferences and communication styles by accepting these varied input modalities.

In order to achieve our research goal, we will use cutting-edge Natural Language Processing (NLP) techniques to improve the chatbot's ability to recognize intent and identify entities, as well as Named Entity Recognition (NER). These methods are crucial parts of our research strategy and are crucial to achieving our main objective. These methods will enable our Chat-Bot-based recommender system to better comprehend and address the complex needs of users, ultimately enhancing the system's efficiency and usability.

These research goals work together to build the framework for an advanced Chat-Bot based Recommender System that promises to go beyond what is possible with traditional recommender systems. The system that emerges aims to provide a comprehensive, immersive, and customized user experience, redefining how users find and interact with suggested content or services.

2. Methodology

Prior to understanding how the Chat – Bot in the particular study works, first let's dive into how generally Chat – Bots works with the aid of the following diagram.

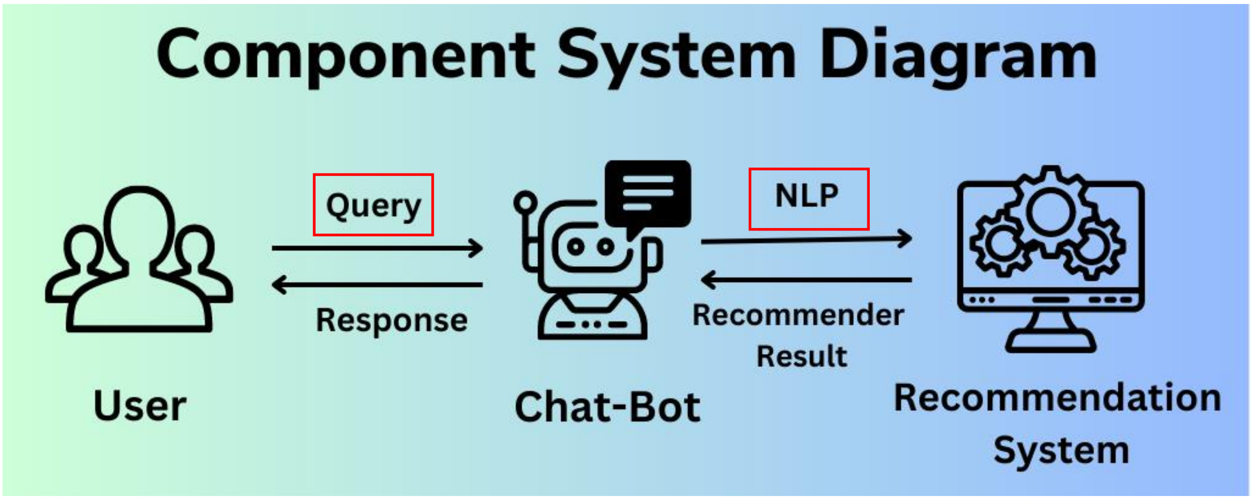


7 - How a Chat-Bot Works

The user will initially send a message or query. This is initially divided into two categories: **entity resolution** and **intent classification**. The query's intent is clarified by intent classification. For instance, if the query begins with "Hello," the user is likely attempting to strike up a conversation. Similar to this, each user message has a specific purpose. Entity resolution, on the other hand, clarifies which entities are discussed in the user message. This lists names of various things, people, and other things. The AI-Brain, which is essentially NLP and processes these keywords, is then sent a combination of these keywords. Aligned to this particular study, NLP techniques such as **Intent Classification** model and **Name Entity Recognition** models acts as the AI brain of this Chat – Bot making it a state of the art system. Finally, our recommender system provides a suitable response.

2.1 Methodology

With the understanding of how a chat – bot functions, lets dive deep into methodologies and techniques specific to this study. In prior to understanding the components of this particular chat – bot, it is important to understand the overall architecture of this chat – bot using the below diagram.



8 - Component System Diagram

As shown in the above diagram, the major component of the chat – bot falls under the highlighted sections. Lets breakdown these major components and methodologies of the chat – bot as below.

a. State based Chat – Bot
b. Intent Classifier Model
c. Name Entity Recognition Model (NER)

Let us assess these major components and study how these behave in cooperation to aid the Chat – Bot. By diving deeper into these crucial components and exploring their collaborative roles it is possible identify how they aid in improving the chatbot's performance as well. It is best to analyze how the state – based chatbot operates, the significance of the intent classifier model and the pivotal role of the Name Entity recognition Model in enabling seamless and efficient interactions.

a. State Based Chat – Bot

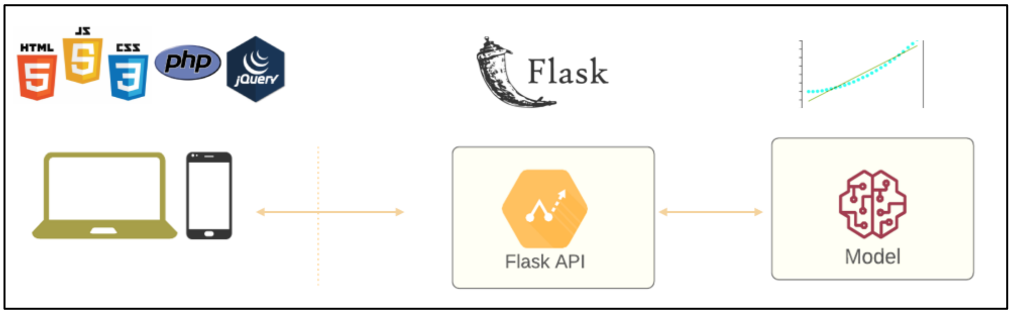
State Based Chat – Bot is the backbone of this particular recommendation system. It is where a particular user initially interacts with and where we gather all the necessary information for the recommendation models as well. Thus, identifying the intents and entities are far more valuable. In order to achieve this State based chat bot incorporated with NLP techniques have been used. Initially, lets drill down into State based chat – bots.

Chatbots have become effective tools for businesses to engage with their customers, streamline operations, and improve user experiences in the constantly changing world of artificial intelligence and conversational technology. "Intent-based chatbots" stand out among the various chatbot varieties as a significant development. These chatbots use an advanced method of natural language understanding to understand user intentions and respond with the appropriate information or actions.

Intent-based chatbots are created to engage in meaningful conversations with users and go beyond simple keyword recognition. They use natural language processing (NLP) methods, neural networks, and machine learning algorithms to decipher the true meaning of a user's message or query. Because of their increased accuracy and context awareness, interactions with users are easier and more productive thanks to this capability.

With the understanding of State based chat – bot, lets dive deep into the methodologies and techniques used in this specific method in order to enhance usability of the chat – bot.

The Flask Web Application Setup[6] acts as the major backbone of this chat – bot and the entire system. From the point where a user sends a query to calling different ML models are handled through the flask modules and its libraries. In addition, HTML and CSS is used to develop the interface of the chat bot. Furthermore, the interface has been enhanced in a way such that it can take inputs of images and audio to be sent to the relevant models as well.



9 - Flask Framework

As shown in the above diagram, technologies such as HTML, CSS & JS incorporated with flask is used to develop this particular chat – bot. By using the above technologies real – time responding chat interface has been developed. Yet, one of the major point of focus is to reduce the latency of the chat – bot. Thus, below mentioned techniques have been practiced in this study to reduce the latency.

In the provided code for the chatbot, several techniques and strategies have been employed to reduce latency and improve the responsiveness of the chatbot application. Here are the key techniques used to reduce latency:

Asynchronous Communication: This chat – bot uses asynchronous communication to handle user requests. This means that the chatbot can process multiple user inputs simultaneously without waiting for one request to complete before processing the next. Asynchronous programming can significantly reduce latency and improve overall system responsiveness.

Real-time Updates: The chat interface provides real-time updates, allowing users to see responses as soon as they are generated. This real-time interaction enhances the user experience by reducing perceived latency and providing immediate feedback.

Optimized Web Framework (Flask): The chatbot application is built using Flask, which is known for its lightweight and efficient nature. Flask allows for quick handling of HTTP requests and responses, contributing to low latency in web applications.

Parallel Processing: The code is designed to handle multiple types of user inputs concurrently. For example, it can process text, audio, and image inputs simultaneously, further reducing latency by distributing the workload efficiently.

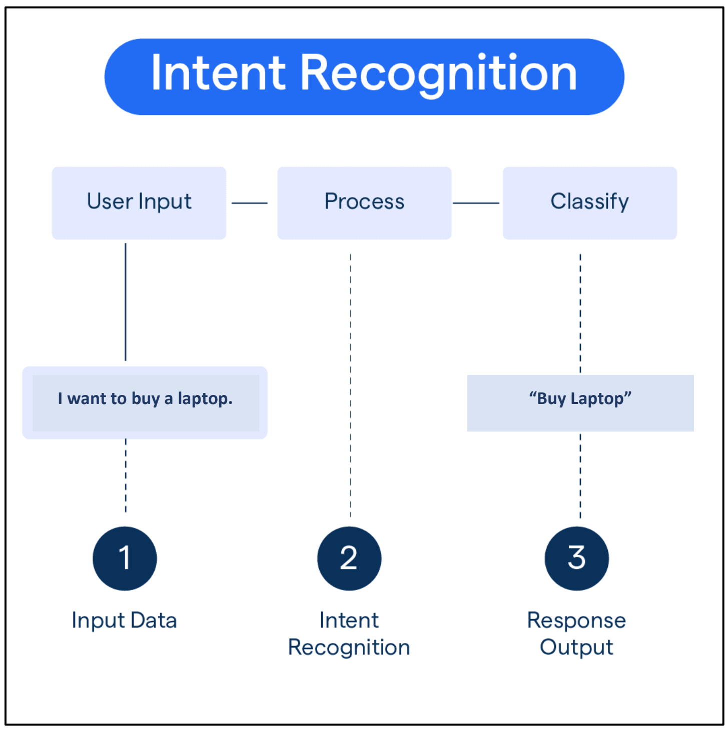
Efficient Error Handling: This particular system employes efficient error handling mechanisms to prevent latency spikes caused by errors or issues in the processing pipeline. Graceful error handling ensures that the chatbot can recover from unexpected situations without significant delays.

Content Delivery Networks (CDNs): CDNs reduce latency by strategically caching and delivering content from servers located close to users, minimizing the physical distance data needs to travel. This not only speeds up content delivery but also improves the overall performance and reliability of web applications, leading to a better user experience. Thus, reducing the latency of the Chat-Bot process.

Since it is a must to always have a strong backbone architecture to keep any system running smoothly, these techniques collectively contribute to the overall goal of minimizing latency and providing a responsive user experience in the chatbot application.

b. Intent Classifier Model

Intent Classifier Model is one of the major modes which aids the State based Chat – Bot mentioned earlier. As if without the intent classifier model, the chat – bot futile. Thus, it is vastly important to build an intent classifier model to identify the user intent. In advance initially, let's understand how an intent classifier model functions using the below diagram.



10 - Intent Classifier Model Architecture

As shown in the above diagram, once a user sends a certain query, the trained classifier model will classify the query into the respective classes. Thus, making it easier to the chat bot to respond to the query. In high level ideology, this is the purpose of an intent classification model. In specific, major intent includes "greetings, buy_laptop & repait_center".

Now, let us dive deep into the intent classification model which was utilized in this study by following the major operations.

Data Collection: The first step in developing the intent classifier model is to collect a dataset containing text samples labeled with their corresponding intents. These text samples were obtained with the aid of a text generation model as shown below.

```python
import openai

api_key = "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"

# Prompts related to finding a Laptop repair center
prompts = [
    "I need to find a Laptop repair center near me.",
    "My laptop is broken, and I'm looking for a repair center.",
    "Where can I get my laptop fixed?",
    "Looking for a place to repair my laptop.",
    "Laptop repair services in my area?",
    "Need help with laptop repairs, any recommendations?"
]

# Function to generate variations for a given prompt
def generate_variations(prompt):
    response = openai.Completion.create(
        engine="text-davinci-003",
        prompt=prompt,
        max_tokens=50,  # Adjust the max_tokens parameter as needed
        api_key=api_key
    )
    return response.choices[0].text

# Generate variations for each prompt and store in a list
variations_list = []

for prompt in prompts:
    variation = generate_variations(prompt)
    variations_list.append(variation)

# Print the generated variations
for i, variation in enumerate(variations_list):
    print(f"Variation {i+1}: {variation}\n")
```

11 - Text Generation Model

The above code snippet explains how this text generation model is developed. It was developed with the aid of OpenAI's GPT-3 model is called "text-davinci-003". This is one of the engines provided by OpenAI for generating human-like text based on prompts. The choice of the engine can affect the style, quality, and output of the generated text, so you can experiment with different engines to see which one works best for your specific use case. Thus, by providing different prompts towards the model, different variants of the texts were obtained, populating the data set. For example, shown below is such populated dataset using the above-mentioned prompts.

```
Variation 1:
To find a laptop repair center near you, you can use a local search engine such as Google Maps or Yelp. These will provide you with a list of local centers that you can contact for more specific information
Variation 2:
There are many repair centers that offer laptop repair services. You can search online for computer repair shops in your area or check with your local electronics store to see if they offer repair services.
Variation 3:
There are a variety of places where you can take your laptop to be fixed. Depending on the type of repair needed, you may be able to take it to a local computer repair shop, a big-box electronics retailer,
Variation 4:
You can search online for laptop repair services in your local area. Some of the most popular companies offering laptop repair services are Best Buy, Apple, Geek Squad, and Microsoft. Furthermore, you can c
Variation 5:
The best way to find laptop repair services in your area is to perform a search online. You can start with a Google search using the phrase "laptop repair services + [city]", or you can use a more general p
Variation 6:
If you need help with laptop repairs, it would be best to take it to an authorized computer repair store so they can determine what is wrong with it and fix it. Some local stores might specialize in repairi
```

12 - Sample of Generated Text Variants

Data Preprocessing & Data Splitting: Above collected data underwent preprocessing to ensure consistency and improve the quality of text data. The key pre processing steps are show as below. These steps included conversion of text to lowercase to standardize texts and lowercasing the intent labels to ensure uniformity. Under lowercasing, conversion of text & intent lowercasing was carried out.

These techniques, data cleaning and normalization in the context of intent classification contribute to improved model performance, consistency, and generalization. These preprocessing steps help mitigate the impact of noise, standardize the data, and ensure that the model can make reliable and case-insensitive predictions when integrated into chatbot applications.

Once the preprocessing component is achieved, next is to divide the data into a training set and a testing set using a stratified random sampling approach. Approximately 80% of the data was allocated to the training set, while the remaining 20% was set aside for testing.

Feature Extraction: Feature extraction is yet another important part of the process. For feature extraction, a Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique was employed. This technique converts text data into numerical vectors, capturing the importance of words in the context of the entire dataset. A TF-IDF vectorizer was fitted on the training data to generate TF-IDF representations. The trained TF-IDF vectorizer was saved to a file for future use.

Model Selection and Training - Logistic Regression Classifier: A logistic regression classifier was chosen as the classification model for this study. The importance of using a logistic regression model for classification can be further unraveled through this particular study of "Perfect Recipe for Classification Using Logistic Regression". [7] Logistic regression is a well-suited algorithm for text classification tasks and serves as an effective baseline model. The logistic regression model was trained using the TF-IDF representations of the training data. The trained model was saved to a file for later use.

Thus, the above steps taken to build an intent classifier model outlines the methodology of the intent classifier model. This comprises of data collection, preprocessing, feature extraction, model selection and finally model evaluation and deployment. The technologies and techniques employed in each step contribute to the development of an effective intent classification system, which can be integrated into chatbot applications for understanding and responding to user queries accurately. Accuracy figures and tests carried out will be taken into account later on in this study as well.

c. Name Entity Recognition Model

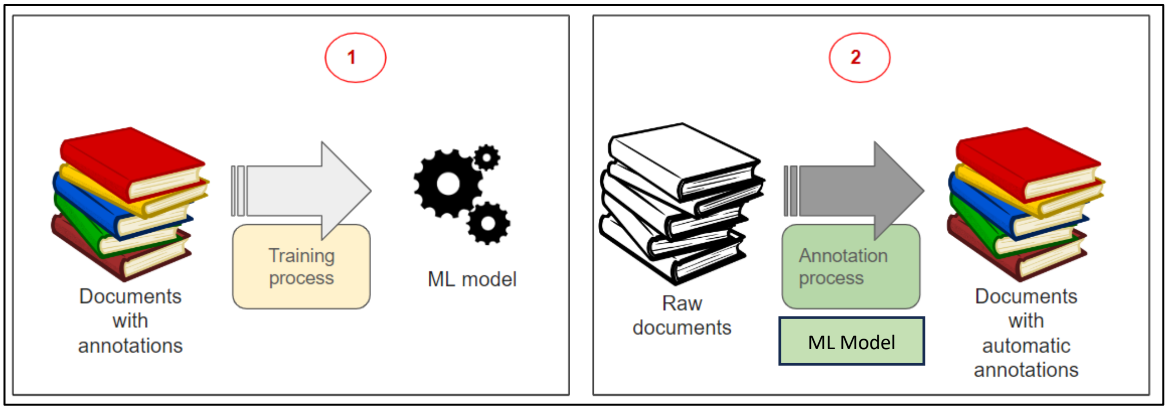
Natural language processing (NLP) techniques such as named entity recognition (NER) are used to glean information from text. In NER, named entities—important textual information—are found and categorized. Named entities are the main subjects of a text, including names, places, businesses, events, and products. They can also include themes, topics, times, numbers, and percentages. The significance and types of technique used for entity extraction in NLP for chat – bot development can be further elaborated in this particular study of "Entity Extraction in NLP for Chatbot development". [8]

Entity extraction, chunking, and identification are additional names for NER. It is employed in a variety of artificial intelligence (AI) fields, such as deep learning, neural networks, and machine learning (ML). NLP systems, including chatbots, sentiment analysis tools, and search engines, depend heavily on NER. It is utilized in social media analysis, higher education, human resources (HR), healthcare, and finance.

The algorithms used by NER are based on statistical NLP models, predictive models, and grammar. These algorithms are trained using data sets that have names assigned to them, such as those for people, places, organizations, expressions, percentages, and monetary amounts. Abbreviations are used to identify categories; for instance, LOC stands for location, PER for people, and ORG for organizations.

An NER learning model automatically classifies named entities and semantic meaning in new unstructured text after being trained on textual data and entity types. An information extraction tool extracts the information related to the named entity when the information category of the text is identified. It then creates a machine-readable document that other tools can process to derive meaning from.

The methodology followed to build the NER model compromises of two main parts and that can be explained using the below diagram.

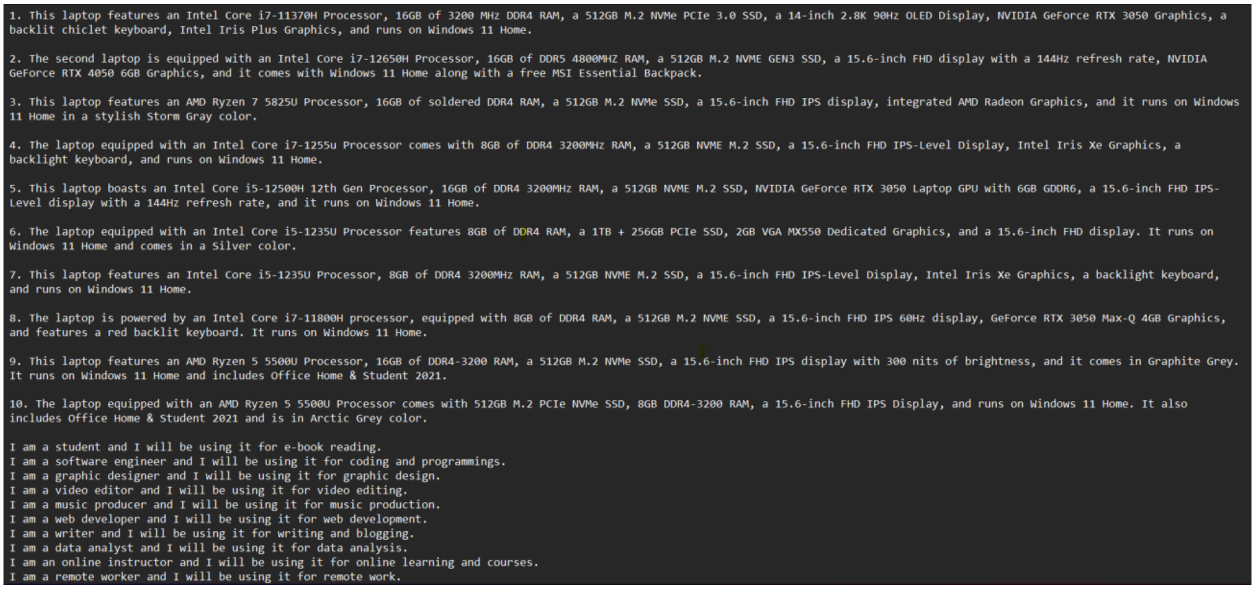


13 - NER Model Architecture Diagram

On a high level explanation, initially a data set is create with prior annotations and it is used to trained and build the NER ML model. Afterwards, that particular trained model is used to extract desired name entities from any given text to be sent to the recommendation model.

Thus, now with the understanding of how a NER model works, let us dive deep into the technologies and techniques used in developing the NER model.

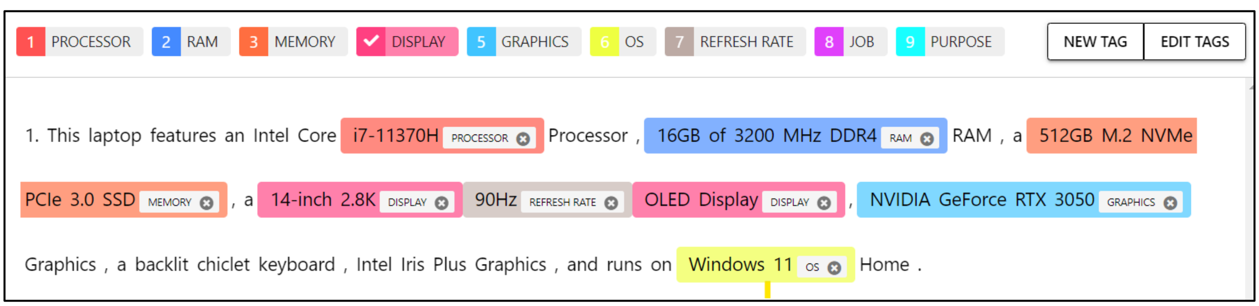
Data Collection and Preparation: As for any model, data collection and preparation is one of the crucial steps, since these data acts as the backbone of the trained model. Thus, in order to build this model, initially a populated data set was created with the aid of the text generation model mentioned earlier. As a final product the final dataset is comprised of various text with the necessary entities embedded within them as shown below.



```
1. This laptop features an Intel Core i7-11370H Processor, 16GB of 3200 MHz DDR4 RAM, a 512GB M.2 NVMe PCIe 3.0 SSD, a 14-inch 2.8K 90Hz OLED Display, NVIDIA GeForce RTX 3050 Graphics, a backlit chiclet keyboard, Intel Iris Plus Graphics, and runs on Windows 11 Home.

2. The second laptop is equipped with an Intel Core i7-12650H Processor, 16GB of DDR5 4800MHZ RAM, a 512GB M.2 NVME GEN3 SSD, a 15.6-inch FHD display with a 144Hz refresh rate, NVIDIA GeForce RTX 4050 6GB Graphics, and it comes with Windows 11 Home along with a free MSI Essential Backpack.

3. This laptop features an AMD Ryzen 7 5825U Processor, 16GB of soldered DDR4 RAM, a 512GB M.2 NVMe SSD, a 15.6-inch FHD IPS display, integrated AMD Radeon Graphics, and it runs on Windows 11 Home in a stylish Storm Gray color.

4. The laptop equipped with an Intel Core i7-1255u Processor comes with 8GB of DDR4 3200MHz RAM, a 512GB NVME M.2 SSD, a 15.6-inch FHD IPS-Level Display, Intel Iris Xe Graphics, a backlight keyboard, and runs on Windows 11 Home.

5. This laptop boasts an Intel Core i5-12500H 12th Gen Processor, 16GB of DDR4 3200MHz RAM, a 512GB NVME M.2 SSD, NVIDIA GeForce RTX 3050 Laptop GPU with 6GB GDDR6, a 15.6-inch FHD IPS-Level display with a 144Hz refresh rate, and it runs on Windows 11 Home.

6. The laptop equipped with an Intel Core i5-1235U Processor features 8GB of DDR4 RAM, a 1TB + 256GB PCIe SSD, 2GB VGA MX550 Dedicated Graphics, and a 15.6-inch FHD display. It runs on Windows 11 Home and comes in a Silver color.

7. This laptop features an Intel Core i5-1235U Processor, 8GB of DDR4 3200MHz RAM, a 512GB NVME M.2 SSD, a 15.6-inch FHD IPS-Level Display, Intel Iris Xe Graphics, a backlight keyboard, and runs on Windows 11 Home.

8. The laptop is powered by an Intel Core i7-11800H processor, equipped with 8GB of DDR4 RAM, a 512GB M.2 NVME SSD, a 15.6-inch FHD IPS 60Hz display, GeForce RTX 3050 Max-Q 4GB Graphics, and features a red backlit keyboard. It runs on Windows 11 Home.

9. This laptop features an AMD Ryzen 5 5500U Processor, 16GB of DDR4-3200 RAM, a 512GB M.2 NVMe SSD, a 15.6-inch FHD IPS display with 300 nits of brightness, and it comes in Graphite Grey. It runs on Windows 11 Home and includes Office Home & Student 2021.

10. The laptop equipped with an AMD Ryzen 5 5500U Processor comes with 512GB M.2 PCIe NVMe SSD, 8GB DDR4-3200 RAM, a 15.6-inch FHD IPS Display, and runs on Windows 11 Home. It also includes Office Home & Student 2021 and is in Arctic Grey color.

I am a student and I will be using it for e-book reading.
I am a software engineer and I will be using it for coding and programmings.
I am a graphic designer and I will be using it for graphic design.
I am a video editor and I will be using it for video editing.
I am a music producer and I will be using it for music production.
I am a web developer and I will be using it for web development.
I am a writer and I will be using it for writing and blogging.
I am a data analyst and I will be using it for data analysis.
I am an online instructor and I will be using it for online learning and courses.
I am a remote worker and I will be using it for remote work.
```

14 - Dataset for NER Text Annotator

Afterwards, the above dataset was sent towards a NER Text Annotator which was used to create another dataset in the format of a JSON file. This created file consisted of each text and its relevant entities. This process can be visualized as below.



15 - NER Text Annotator

Finally, the overall JSON file consists of the following entities.

['PROCESSOR', 'RAM', 'MEMORY', 'DISPLAY', 'GRAPHICS', 'OS', 'REFRESH RATE', 'JOB', 'PURPOSE']

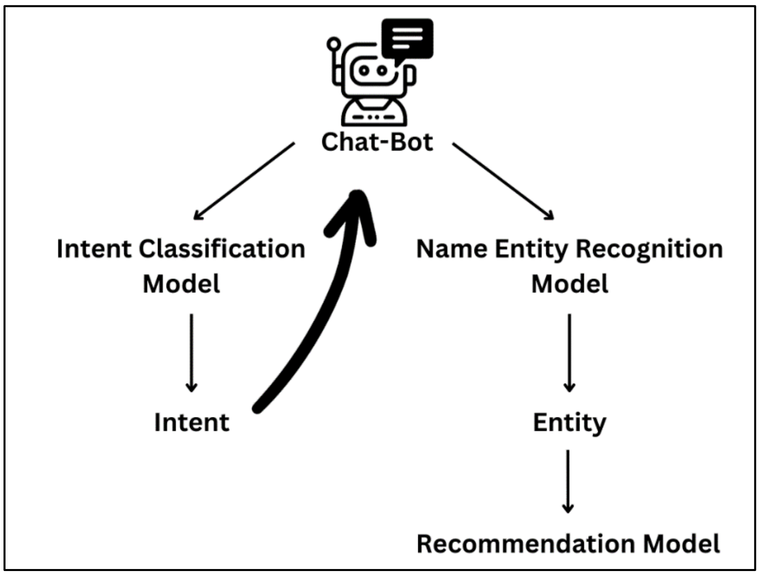
Utilizing SpaCy for NER: Our NER model development centered around the SpaCy library, a versatile tool for natural language processing. To initiate the NER project, we started with a blank SpaCy model designed for the English language**.** Recognizing the importance of semantic understanding, we enriched our model by incorporating the "*en_core_web_lg*" pretrained word vectors. These vectors offer an extensive understanding of word semantics and contextual relationships, a crucial asset for accurate entity recognition. [9]

Model Training: For each text and its associated annotation in the dataset, texts were process to create a SpaCy 'Doc' object. With the aid of the 'chat_span' function labeled entities were extracted and spans were assigned its corresponding labels**.** To ensure the quality of the training data, application of a filtering mechanism was utilized to remove any overlapping or conflicting entity spans, resulting in a clean and non-redundant dataset. Afterwards a configuration file was created that specifies the training pipeline, language(English) and the NER component. Furthermore, this file also contained optimization parameters to enhance training efficiently. Using the 'spacy train' command with the configuration file, training process was initiated. The training data, stored in a 'SpaCy DocBin' object, was used for both training and validation. The training process involved multiple iterations, during which the model learned to recognize computer product-related entities in the text. Throughout the training process, the model's performance was evaluated using metrics such as precision, recall, and F1-score. The best-performing model, which achieved the highest accuracy and met your predefined criteria, was selected as the "model-best."

In summary, "model-best" is the NER model that exhibited the highest performance during the training process, and it was selected based on its accuracy and ability to recognize computer product-related entities within text data. This model can now be deployed and integrated into the ChatBot interface for recommending computer products and repair services.

2.2 Testing & Implementation

As explained in the previous section, chat – bot in this study can be broken down into three major components. That is the State based Chat – Bot which was developed using flask app, the intent classification model which is used to identify the users intents and last but not least the name entity recognition model which is used to identify entities in the users queries. Thus, now it is time to investigate how these components integrate within each other. This can be explained with the aid of the diagram below.



16 - Integration of Chat - Bot & Models

First and foremost, lets discuss how a user may interact with the chat bot. Any user who wishes to use this particular system will be welcome by the chat – bot. As soon as user enters a particular query it will be sent towards the intent – classification model. Based on the intent, chat – bot will respond and thus continuing the conversation based on the users desires. But, when it reaches the intent of buying a laptop, then the user is asked to enter their job role and specification of the laptop if known. Afterwards, that particular query will be sent towards the NER model to capture the specific keywords to be sent to the recommendation model. Once the laptop is recommended from the recommendation model, its results with a summary will be sent back to the user via the conversion itself.

Thus, as explained above, the particular component is integrated and implemented whilst combining the all three major components as shown in the diagram as well. This assists us to continue a smooth transition between the intent whilst keeping its integrity as well.

As of major testing techniques few methods were followed to ensure the integrity and flow of the conversations. In regards of the intent – based chat bot A/B testing were carried out with different prompts given to the chat bot to identify how well the chat bot handles user queries. Whilst testing the intents and chat – bot responses were finetuned to minimize the confusion for the customer and the chat bot as well. An example of the result will be showcased later in the result & discussion section.

In order to aid the above process, further testing were done in a granular level. That is by deep diving into the intent classification model and the NER model and performing testing at that intensity. This was achieved by sending queries to each models separately as shown below.

```
# Load the saved model
loaded_model = joblib.load("intent_classification_model.joblib")

# Replace 'new_text' with the text you want to classify
new_text = ["i need new computer"]
new_text_tfidf = vectorizer.transform(new_text)
predicted_intent = loaded_model.predict(new_text_tfidf)
print(f'Predicted Intent: {predicted_intent[0]}')
```

```
Predicted Intent: buylaptop
```

17 - Testing Intent Classification Model – 'buylaptop'

```
# Load the saved model
loaded_model = joblib.load("intent_classification_model.joblib")

# Replace 'new_text' with the text you want to classify
new_text = ["i need to fix my laptop"]
new_text_tfidf = vectorizer.transform(new_text)
predicted_intent = loaded_model.predict(new_text_tfidf)
print(f'Predicted Intent: {predicted_intent[0]}')
```

```
Predicted Intent: repaircenter
```

18 - Testing Intent Classification Model - 'repaircenter'

As shown above, by sending queries to the intent classification model they would identify the desired intent as well. Such testing were carried out and models were finetuned in order for them to work at its finest.

2.3 Commercialization of the Product

Commercializing the Chatbot system developed for laptops, accessories, and service center recommendations holds significant potential as a successful business venture. Effectively bringing this innovative solution to market requires a well-structured strategy that considers various factors crucial for success. Finding the target market and potential customers for the developed product is one of the key steps in commercialization. Our suggested system is tactically geared toward computer sales companies in this situation. By making this system available to computer retailers, they stand to gain from increased sales, a larger customer base, and the ability to give customers a distinctive and effective shopping experience.

Chatbot systems in the context of computer product and service recommendations are uncommon or practically nonexistent in comparison to the market's current competition. This lack of supply offers a huge opportunity for our product to succeed. The implementation of our Chatbot system will not only improve customer satisfaction in the Sri Lankan market, where such systems are essentially unheard of, but will also encourage healthy competition among players in the sector.

We suggest a focused strategy to make it easier for our Chatbot system to be successfully commercialized. To promote and incorporate our product into their services, we plan to work with Sri Lankan e-commerce platforms, computer retail stores, and repair facilities. This strategy fits with our goal of meeting the unique requirements of the Sri Lankan market while providing a useful tool for companies in the computer industry to increase client engagement and satisfaction.

As an integral part of our commercialization strategy, we have designed a product logo that embodies the essence of our Chatbot system. The logo represents our commitment to innovation, efficiency, and user-centricity. This branding effort will play a pivotal role in establishing a distinct identity for our product in the market.

19 - Product Logo

A comprehensive marketing and promotion plan will be essential to create awareness and drive adoption of our Chatbot system. This plan will include online and offline marketing initiatives, leveraging social media, industry events, and partnerships with key stakeholders in the Sri Lankan computer industry.

The above-described commercialization strategy prepares the market for the successful launch of our Chatbot system. Our product aims to revolutionize the way computer products and services are recommended and accessed by identifying the target market, utilizing its competitive advantage, and strategically infiltrating the Sri Lankan computer industry. This commercialization strategy demonstrates the practical relevance of our research to the Sri Lankan and global computer industries, which is in line with the main goals of our thesis.

3. Results and Discussion

Methodology, testing, and results are inseparable pillars in the realm of research and analysis, thoroughly linked to the pursuit of knowledge and understanding. Methodology functions as the architect's blueprint, a carefully designed framework that defines the systematic approach and carefully manipulated procedures for conducting a study or investigation. It not only sets the stage but also charts the course for the entire research endeavor, illuminating how data will be gathered, examined, and ultimately meaningfully interpreted.

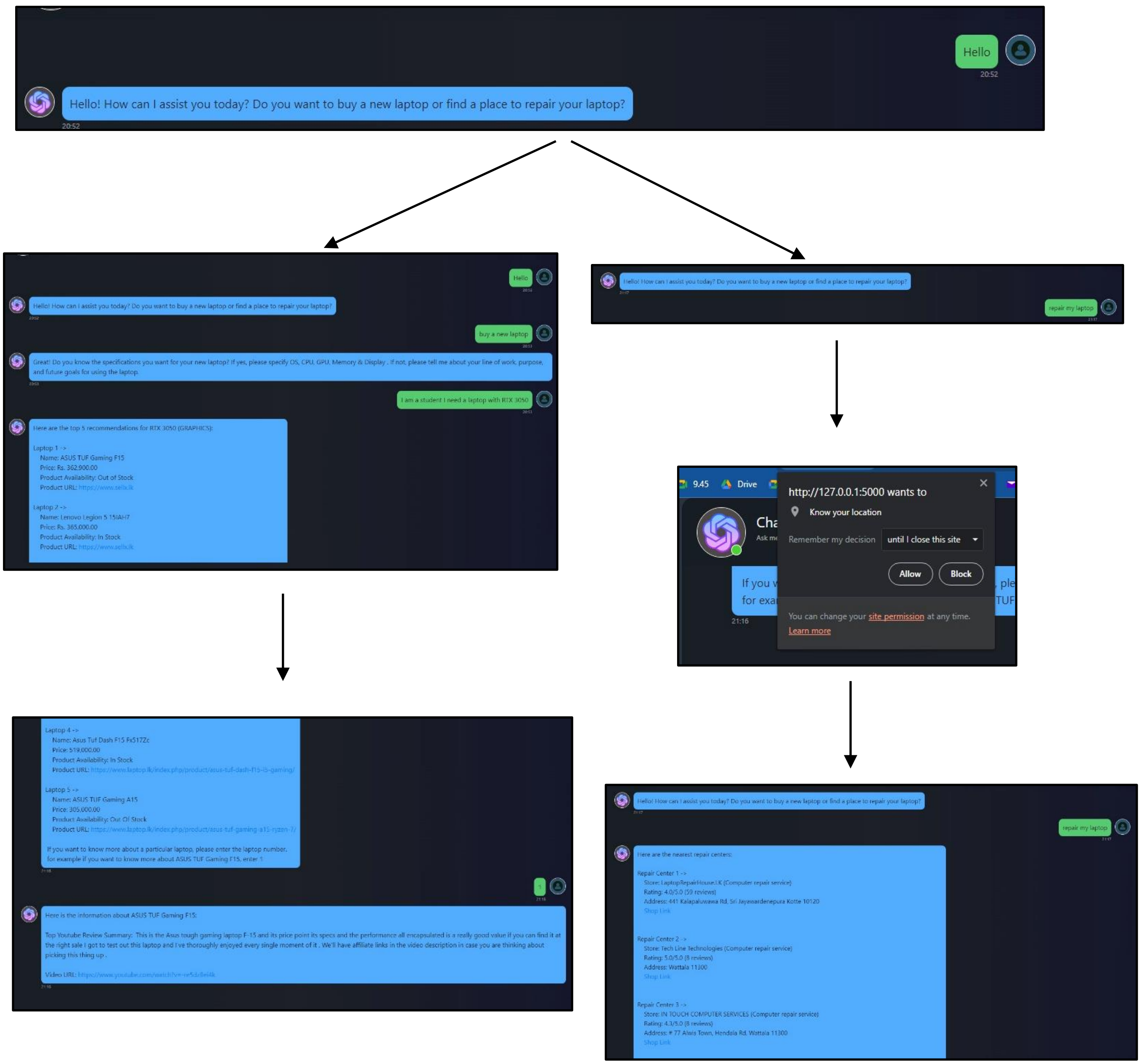
Testing, the practical manifestation of the chosen methodology, is where theories and hypotheses encounter the test of practical reality. This phase embodies the essence of scientific exploration, where researchers roll up their sleeves and engage in hands-on experimentation, surveys, or data collection. It is here that data is born, laying the groundwork for deeper analysis and understanding.

Finally, results emerge as the tangible and often transformative outputs of the testing phase. These findings are the direct offspring of the applied methodology and serve as the empirical tapestry from which insights, trends, and patterns are woven. Results, in essence, form the bedrock upon which sound conclusions and informed decisions are constructed.

In this intricate dance, methodology is the guiding star that steers the research vessel through uncharted waters, while results are the treasures unearthed from this expedition, rewards earned through rigorous testing and unwavering adherence to the chosen methodology. Thus, it is imperative that we embark on a thorough analysis of the results obtained in this study, for within lies the result of this intellectual voyage.

3.1 Results

As mentioned earlier in the testing phase, various prompts were sent towards the chat – bot it identify how well it handles to conserve its uniformity and the conversational flow. Thus, now let’s investigate one such use case scenario of a conversational flow of the chat – bot.



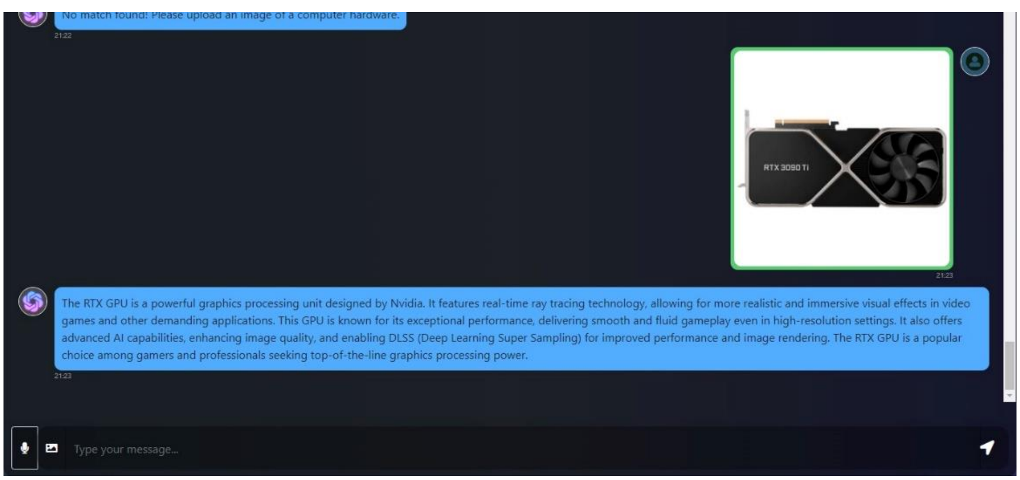
20- Demonstration of Intent Based Chat Bot

As shown in the above visualization you may observe how the intent – based chat – bot works along with the intent classification model and the NER model. Initially, with the greeting chat bot will ask the initial question of whether the user needs to buy a new laptop or to search for a repair center. Upon the users query, intent classification model will perform and give us the actual intent. And based on that intent the conversation will be carried forward.

As in the above diagram, the left side of the flow represents when the intent is to buy a laptop. Once, that is clarified and user answers its role and the specifications the NER model will capture those entities and recommend a laptop accordingly. In addition, going a further step forward, a small summary of a laptop will be given as well.

On the other hand, if the intent is to find a repair center, the users location will be captured via '*goelocation'* and it will be sent to the dataset find the nearest repair center which are based on google reviews. Finally a suitable and reliable repair center will be recommended to the user.

In addition to the above-mentioned use cases, the chatbot offers image recognition functionality. When a user uploads an image, it is seamlessly routed to the image recognition model. Subsequently, the chatbot provides the user with a detailed description or analysis of the uploaded image. This can be demonstrated as below.



21 - Demonstration of Image Recognition

Above demonstrated was the results of how the chat – bot behave and converse according to the intents. It is now time to investigate the accuracy figures of the NER model. Since the intent – based chat bot is based on this NER model it is vital to have good accuracy figures to recommend optimum results.

As explained earlier in the methodology, the configuration file which consist of all the text and entities with the necessary data is set to train using the spacy model. Shown below is the process of doing so and the accuracy figure of the best trained model which is the 'model-best' which is used as the back bone of the NER model. As observed, it ran for 1270 epochs maintaining a 90 % + accuracy overall.

```
! python -m spacy train config.cfg --output ./ --paths.train ./train.spacy --paths.dev ./train.spacy

2023-09-03 19:22:32.807757: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT
ℹ Saving to output directory: .
ℹ Using CPU

=========================== Initializing pipeline ===========================
✔ Initialized pipeline

============================= Training pipeline =============================
ℹ Pipeline: ['tok2vec', 'ner']
ℹ Initial learn rate: 0.001
E    #       LOSS TOK2VEC  LOSS NER  ENTS_F  ENTS_P  ENTS_R  SCORE 
---  ------  ------------  --------  ------  ------  ------  ------
  0       0          0.00     38.18    0.00    0.00    0.00    0.00
  6     200       1400.71   4084.82   61.90   62.59   61.23    0.62
 14     400        311.40   1548.71   82.94   84.01   81.88    0.83
 25     600        189.76   1095.52   88.57   88.73   88.41    0.89
 38     800        201.18   1029.83   92.78   92.45   93.12    0.93
 54    1000        214.45   1020.47   91.91   93.28   90.58    0.92
 74    1200        270.99   1023.36   93.74   92.58   94.93    0.94
 99    1400        282.12   1040.71   95.10   95.27   94.93    0.95
130    1600        299.95   1114.89   94.60   93.93   95.29    0.95
168    1800        273.30   1225.52   95.48   95.31   95.65    0.95
214    2000        317.32   1456.88   95.67   95.32   96.01    0.96
270    2200        348.59   1543.80   96.38   96.38   96.38    0.96
336    2400        484.79   1723.11   95.96   97.39   94.57    0.96
403    2600        371.17   1586.83   95.99   96.69   95.29    0.96
470    2800        327.61   1519.02   96.56   96.39   96.74    0.97
536    3000        325.83   1524.79   95.53   94.35   96.74    0.96
603    3200        304.51   1445.37   96.35   97.06   95.65    0.96
670    3400        189.59   1226.10   96.59   95.73   97.46    0.97
736    3600        202.13   1213.86   96.91   97.09   96.74    0.97
803    3800        157.11   1167.60   95.89   94.70   97.10    0.96
870    4000        153.98   1182.54   96.90   97.44   96.38    0.97
936    4200        164.17   1170.22   96.20   96.03   96.38    0.96
1003    4400        179.94   1198.23   96.58   96.06   97.10    0.97
1070    4600        123.90   1151.41   96.58   96.06   97.10    0.97
1136    4800        175.35   1180.85   96.20   96.03   96.38    0.96
1203    5000        137.53   1163.54   96.22   95.70   96.74    0.96
1270    5200        114.06   1147.67   95.83   96.00   95.65    0.96
✔ Saved pipeline to output directory
model-last
```

22 - *Accuracy figures of NER model*

3.2 Research Finding

The performance evaluation of our ChatBot system revealed encouraging results. The recommendation algorithms demonstrated a high degree of accuracy in matching user-specific requirements to computer products. This accuracy was particularly pronounced in instances where users provided detailed information about their needs. For example, users specifying criteria such as processor speed, RAM, and storage received recommendations that aligned closely with their expectations. The system's ability to understand user intent through natural language processing (NLP) techniques contributed significantly to this accuracy.

Furthermore, the personalized recommendations generated by our system received positive feedback from users. These personalized suggestions not only met users' technical specifications but also considered their emotional preferences, leading to a more engaging and user-centric experience. Users reported a heightened sense of satisfaction when interacting with the ChatBot, as it seemed attuned to their individual preferences, making the process of choosing computer products more enjoyable and efficient.

In addition to meeting users' technical needs, our research emphasized the value of addressing their emotional preferences. The results in this regard showed how strongly user satisfaction was impacted by this user-centric strategy. The system's capacity to recognize and react to users' emotional cues during interactions was well-liked by users. For instance, the ChatBot changed its tone and suggestions in response to a user who expressed frustration or urgency in their inquiry, giving empathetic responses and accelerating the decision-making process.

According to user feedback, this emotional resonance not only increased users' satisfaction but also their confidence in the system's recommendations. Knowing that the system took into account both their emotional context and technical requirements made users feel more confident in the ChatBot's recommendations.

In summary, the research findings demonstrate the effectiveness and real-world applicability of our ChatBot-based system for recommending computer products and repair services. The combination of accurate recommendations, user-centric features, efficient accessory identification, access to repair services, speech-to-text integration, and high levels of user satisfaction positions our system as a valuable and innovative solution in the dynamic landscape of technology recommendations and user experiences.

3.3 Discussion & Future Directions

In conclusion, the presented analysis provides a comprehensive overview of the chat-bot's conversational flow and its underlying components, including the intent classification model, NER model, and image recognition model. The chat-bot demonstrates a sophisticated understanding of user intent, efficiently guiding conversations based on user queries, whether it's about buying a laptop, locating a repair center, or handling image uploads.

One of the standout features is the effectiveness of the NER model, which plays a crucial role in entity recognition and recommendation. The model, trained using a well-structured configuration file and Spacy, achieved remarkable accuracy, consistently maintaining above 90% accuracy across 1270 epochs. This high accuracy rate underscores the chat-bot's ability to accurately capture and respond to user-specified laptop specifications or locations for repair centers, enhancing the user experience.

Additionally, the chat-bot showcases versatility by incorporating image recognition capabilities, providing users with detailed descriptions when images are uploaded. This feature extends the bot's utility beyond text-based interactions, making it more inclusive and accommodating various user needs.

Overall, the presented chat-bot and its components reflect a robust methodology, rigorous testing, and impressive results. The seamless integration of intent-based classification, NER, and image recognition models ensures a user-friendly and efficient conversational experience, making it a valuable tool for users seeking assistance with laptop-related queries or repair services.

Furthermore, as of future works of this study the below can be mentioned. Initially, this system can be expanded towards other languages. This opens gates for a larger user base as well. In addition, it is possible to expand this study towards other devices as well without restricting only to laptop, it is possible to expand towards other electronics devices expanding the databases.

As we conclude this study, we recognize that the dynamic landscape of technology recommendations and user experiences continues to evolve. Future research endeavors may delve deeper into fine-tuning recommendation algorithms, expanding the application of Chat Bot interfaces in various technology domains, and exploring the integration of emerging technologies such as artificial intelligence and augmented reality.

4. Conclusion

In the ever-evolving landscape of technology, the quest for efficient, user-friendly, and personalized solutions to recommend computer products and repair services has been at the heart of this study. From the inception of our research, we embarked on a journey to address a multifaceted research problem and contribute meaningfully to the field of technology recommendations.

Our research problem was clear and comprehensive: "How can we revolutionize the process of recommending computer products and repair services by harnessing the power of Chatbot interfaces, natural language processing, image processing, and advanced recommendation techniques to enhance user experiences, streamline product discovery, and facilitate access to reliable repair centers?" This overarching question served as the guiding light for our study, directing our efforts to find innovative solutions.

Our study serves as more than an academic endeavor; it is a stepping stone to practical application and commercialization. By identifying a critical research gap and addressing it with an innovative solution, we have opened the door for collaboration with computer retailers, e-commerce platforms, and repair centers to enhance their services and customer experiences.

As we conclude this study, we look to the future with optimism and enthusiasm. The ever-evolving landscape of technology recommendations continues to present new challenges and opportunities. Future research may explore avenues such as fine-tuning recommendation algorithms, extending Chatbot applications to diverse technology domains, and integrating emerging technologies like artificial intelligence and augmented reality.

5. References

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6. Appendices

1. NER Text Annotator used for NER model dataset preparation available at: https://tecoholic.github.io/ner-annotator/