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**DocBot: Elevating Health Information Access with Advanced Neural Networks**

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The thesis titled “DocBot: Elevating Health Information Access with Advanced Neural Networks” has been submitted to the following respected members of the board of examiners of the department of computer science in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science on 10 June 2024 and has been accepted as satisfactory.

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List the significant and substantial inputs made by different authors to this research, work and writing represented and/or reported in the thesis. These could include significant contributions to the conception and design of the project; non-routine technical work; analysis and interpretation of research data; drafting significant parts of the work or critically revising it to contribute to the interpretation.

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## Abstract

This paper dives into the application of neural network techniques for the development of an advanced chatbot system named DocBot, aiming at giving intuitive medical support. Neural networks have emerged as a cornerstone technique in natural language processing (NLP) and text categorization, revolutionizing applications such as sentiment analysis, language comprehension, and chatbot building. The architecture of neural networks, encompassing input, hidden, and output layers, promotes the transformation of raw text data into meaningful predictions by recognizing subtle patterns and connections within the input. The development method of DocBot comprises numerous stages, including data preparation, model training, and integration into an application interface. By employing techniques such as tokenization, stemming, and bag-of-words representation, DocBot preprocesses textual material to promote correct understanding and answer production. The deployment of a feedforward neural network model, trained on a selected dataset including patterns and related tags, enables DocBot to anticipate human intents with surprising accuracy. Through the training progress of the neural network model, indicated by the drop in loss values across epochs, significant learning and adaptation are demonstrated. The graphical user interface (GUI) of DocBot is designed to give a user-friendly platform for accessing medical information, incorporating clear communication prompts and orderly presentation of responses. From welcoming messages to answering sophisticated medical queries, the GUI stresses simplicity, clarity, and reactivity, boosting the overall user experience. The incorporation of neural network techniques in the building of DocBot suggests a big advancement in AI-driven healthcare aid. By utilizing the power of deep learning models, DocBot exhibits extraordinary capabilities in interpreting and processing human language, hence permitting smooth interactions between humans and the system. As AI continues to evolve, DocBot stands as a testament to the transformational potential of neural network technology in changing healthcare communication and information sharing.

## Keywords

Neural networks, chatbot, natural language processing, text categorization, deep learning, medical assistance, graphical user interface, model training, data preprocessing, user interaction

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# List of Abbreviations and Symbols

Abbreviations

Abbreviations and Symbols:

NLP Natural Language Processing

GUI Graphical User Interface

ReLU Rectified Linear Unit

API Application Programming Interface

JSON JavaScript Object Notation

LSTM Long Short-Term Memory

CNN Convolutional Neural Network

NN Neural Network

PyTorch Python-based scientific computing library

NLTK Natural Language Toolkit

URL Uniform Resource Locator

HTML Hypertext Markup Language

CSS Cascading Style Sheets

HTTP Hypertext Transfer Protocol

HTTPS Hypertext Transfer Protocol Secure

URL Uniform Resource Locator

LSTM Long Short-Term Memory

CNN Convolutional Neural Network

API Application Programming Interface

HTTP Hypertext Transfer ProtocolNLP Natural Language Processing

*etc. etc.*

**Chapter1**

# Introduction

## 1.1 Background

The rise of artificial intelligence, especially the progress of neural network models, has ushered in a transformational era in natural language processing (NLP) and text classification. This technical progress has sprouted breakthrough applications, like chatbots, sentiment analysis, and language understanding, emphasizing the versatility and endurance of neural networks in handling varied tasks related with textual data. In the healthcare arena, the inclusion of such cutting-edge technology provides a potential prospect for supporting consumers with questions linked to disorders. With a rising demand for accessible and credible health information, there exists a significant need for intelligent systems capable of comprehending and reacting to user questions concerning particular medical problems. Neural network models, with their ability to comprehend subtle patterns in textual material, present a vital possibility to enhance the efficiency and accuracy of these systems [5]. The complex nature of medical queries demands a nuanced understanding of language, context, and domain-specific knowledge, which traditional rule-based systems often struggle to achieve. However, neural networks excel in capturing intricate relationships within textual data, allowing them to interpret user queries and provide relevant responses with a high degree of accuracy.

This potential breakthrough offers promise for the development of enhanced healthcare support technologies, bridging the gap between users and complete, context-aware information. Imagine a scenario where individuals can interact with a chatbot to inquire about symptoms, treatment options, or even preventive measures for various medical conditions. By leveraging neural network models, these chatbots can analyze vast amounts of medical literature, clinical guidelines, and patient data to offer personalized recommendations tailored to each user's unique needs and preferences. Moreover, the integration of neural network models in healthcare extends beyond just information retrieval and recommendation systems [5]. It opens up avenues for advanced applications such as disease diagnosis, prognosis prediction, and treatment optimization. By analyzing patient data, including medical records, imaging scans, and genetic information, neural network models can assist healthcare professionals in making more informed clinical decisions, leading to improved patient outcomes and quality of care.

As we witness the dynamic landscape of artificial intelligence intersecting with healthcare, the integration of neural network models not only addresses the current demand for reliable health information but also paves the way for a future where intelligent systems play a central role in facilitating user interactions and providing nuanced insights into complex medical queries. The synergy between advanced technology and healthcare expertise holds the potential to revolutionize the way we approach healthcare delivery, making it more accessible, efficient, and personalized to individual needs. However, it is essential to address challenges such as data privacy, ethical considerations, and algorithmic bias to ensure the responsible and equitable deployment of these technologies in healthcare settings.

## 

## 1.2 Problem Statement

In the dynamic world of healthcare, where consumers actively seek information and assistance on varied medical issues such as heart disease and diabetes, the limits of current platforms become clearer. The contextual intricacies included in health-related questions sometimes transcend the capability of traditional systems, resulting in a gap in understanding and individualized reaction. Traditional techniques, depending on preset rules and unsophisticated algorithms, fail to give correct and personalized replies, sometimes leading to misunderstandings or misinterpretations of crucial health information. This highlights the requirement for a paradigm change in the design and functioning of healthcare support systems. The existing landscape of disease-related question-answering systems reveals a gap in capturing the full potential of sophisticated neural network models. These advanced models, with their potential to understand complicated patterns and contextual nuances within textual data, provide a transforming answer to the complexity inherent in medical queries. The suggested DocBot stands as a new answer to this unmet demand, proposing to utilize the capability of neural networks to enhance its comprehension and response skills within the dynamic domain of health-related queries [6].

DocBot, as a sophisticated system, intends to overcome the current gap by applying state-of-the-art neural network models. This includes not just grasping the surface-level components of textual input but also digging into the subtle linkages and contextual information essential for correct health-related answers. The employment of neural networks is a shift from conventional rule-based techniques, allowing DocBot to adapt, learn, and grow in concert with the ever-expanding field of medical knowledge and user requests. The critical need for such a system is clear in the potential influence on user empowerment and healthcare accessibility. By using powerful neural network models, DocBot aspires to deliver not only information but intelligent and individualized recommendations targeted to particular health needs [7]. This proactive strategy strives to promote user knowledge, facilitate informed decision-making, and eventually lead to better health outcomes.

In this endeavor, the proposed investigation and implementation of DocBot constitute a critical step towards addressing the unmet expectations for intelligent, adaptable, and user-centric healthcare assistance technologies. DocBot's potential impact extends beyond just answering user queries; it has the capability to transform the way individuals interact with healthcare information and services. By providing personalized recommendations based on individual health profiles, DocBot empowers users to take control of their health journey. This personalized approach fosters a sense of ownership and responsibility, leading to increased engagement in preventive care and proactive health management.Moreover, DocBot's ability to continuously learn and adapt ensures that it remains up-to-date with the latest medical research, guidelines, and best practices. This dynamic nature enables DocBot to evolve alongside the ever-changing landscape of healthcare, ensuring that users receive accurate and relevant information at all times. Furthermore, DocBot serves as a valuable tool for healthcare professionals, augmenting their clinical decision-making process and streamlining patient interactions. By assisting with information retrieval, symptom assessment, and treatment recommendations, DocBot alleviates the burden on healthcare providers, allowing them to focus on more complex and critical aspects of patient care.**Top of Form**

## 1.3 Objectives of the Study

In the ever-evolving environment of healthcare technology, the integration of powerful artificial intelligence has become important. This research aspires to contribute to this revolutionary journey by presenting DocBot, a specialized question-answering system employing neural network models. The following goals describe the road towards strengthening its effectiveness in understanding and responding to disease-related questions. Specific objectives include:

* Develop and install DocBot, a customized question-answering system leveraging sophisticated neural network models for increased interpretation of disease-related questions.
* Investigate and enhance the neural network architecture inside DocBot, leveraging deep learning for optimal health-related text processing.
* Improve user engagement by enhancing DocBot's capacity to participate in natural and contextually relevant discussions.
* Conduct extensive studies to examine the accuracy and efficacy of DocBot in giving credible information about illnesses, comparing its performance with current systems and conventional approaches.
* Contribute insights and breakthroughs to the development of intelligent healthcare assistance technologies by exhibiting the potential of neural network models in effectively handling disease-related questions.

## 1.4 Scope of the Study

The scope of this research extends far beyond the conventional limitations of healthcare support systems, delving into the realm of artificial intelligence (AI) and its transformative potential in addressing disease-related concerns. Through a concentrated effort on the creation and refinement of DocBot, a specialized question-answering system, this research endeavors to pioneer breakthroughs in user interface design, information accuracy, and the broader landscape of intelligent healthcare solutions. At its core, this research seeks to broaden the horizons of current question-answering systems by introducing DocBot as an innovative alternative. DocBot transcends the constraints of traditional techniques by harnessing the power of advanced neural network models to comprehend and respond to complex and context-specific health-related inquiries. In an era where the demand for accurate, tailored, and accessible healthcare information is on the rise, DocBot's enhanced capabilities are indispensable in meeting the evolving needs of users within the healthcare domain.

A significant aspect of this research lies in the exploration of neural network design within DocBot. By investigating methodologies such as word embeddings and deep learning, the research aims to achieve a sophisticated understanding of the semantic significance of medical information. Through iterative refinement of the design, this research contributes to the broader field of AI, showcasing how these cutting-edge technologies can improve the interpretation of intricate healthcare data and facilitate more informed decision-making processes. However, the research's focus extends beyond technological advancements alone and encompasses the realm of user experience (UX) design. Recognizing the pivotal role of user engagement in the success of healthcare support systems, this research endeavors to make DocBot more than just an information repository. By enabling natural and contextually relevant interactions, recognizing user intent, and adapting to various language nuances, this research anticipates a transformative impact on how users engage with and derive value from healthcare support products.

Furthermore, the assessment of DocBot's accuracy and efficacy adds a critical dimension to the scope of this research. Through rigorous comparisons with existing systems and traditional approaches, insights into DocBot's performance are gained, guiding future enhancements in the sector. By evaluating DocBot's performance against established benchmarks, this research contributes not only to the narrow domain of disease-related question-answering but also to the broader landscape of intelligent healthcare assistance systems. Moreover, this research aims to address critical challenges and limitations encountered in existing healthcare support systems. These challenges include issues related to information accuracy, scalability, and user accessibility. By developing DocBot as a robust and versatile solution, this research endeavors to overcome these obstacles and pave the way for more effective and user-centric healthcare support technologies. This research seeks to push the boundaries of intelligent healthcare solutions by developing and enhancing DocBot, a specialized question-answering system powered by advanced neural network models. Through a multidimensional approach encompassing technological innovation, user experience design, and performance evaluation, this research aims to contribute to the advancement of the healthcare industry and improve the delivery of healthcare services to individuals worldwide.**Top of Fo**

## 1.5 Significance of the Study

In the ever-evolving landscape of healthcare support tools, the emergence of DocBot stands as a beacon of innovation. This specialized question-answering system, powered by robust neural network models, holds immense promise in revolutionizing the way individuals access and interact with medical information. The significance of this research transcends mere technological advancements; it embodies a paradigm shift in healthcare accessibility, efficacy, and user experience. At the heart of its relevance lies the escalating demand for intelligent systems capable of deciphering and responding adeptly to a myriad of disease-related inquiries. With the proliferation of health-related information on the internet, individuals often encounter hurdles in obtaining reliable and tailored insights into their specific medical concerns. DocBot, leveraging the capabilities of neural network models, endeavors to bridge this crucial gap, offering consumers a trustworthy and intuitive resource for navigating complex medical knowledge. In a world inundated with data, DocBot's ability to distill and deliver pertinent information efficiently holds profound implications for healthcare seekers, practitioners, and researchers alike.

Moreover, the focus of this study on unraveling and enhancing neural network design significantly enriches the broader discourse on artificial intelligence in healthcare. Neural networks serve as indispensable tools for discerning subtle patterns and semantics within textual data, thereby laying the foundation for sophisticated healthcare assistance systems. By advancing our understanding of neural network architecture and optimization techniques, this research paves the way for more robust and efficient healthcare solutions. In an era where the convergence of technology and healthcare is imperative for delivering effective and accessible medical services, the insights gleaned from this study assume paramount importance. A pivotal aspect of DocBot's relevance lies in its capacity to enhance user engagement, particularly within the realm of human-computer interaction in healthcare. By facilitating natural and contextually relevant conversations, discerning user intent, and accommodating diverse language variations, DocBot strives to enrich the user experience manifold. This is particularly salient for individuals seeking medical information, as it empowers them with a seamless and personalized interface with the system. The ability of DocBot to establish meaningful rapport with users not only fosters trust and confidence but also fosters a deeper level of engagement with healthcare information—an aspect critical for promoting informed decision-making and proactive health management.

Furthermore, the emphasis placed on rigorously evaluating the accuracy and efficacy of DocBot adds another layer of relevance to this study. In the realm of healthcare, misinformation or errors can have dire consequences. Through systematic testing and comparison with existing systems and conventional approaches, this research endeavors to establish benchmarks and best practices in the development of intelligent healthcare support technologies. By meticulously assessing DocBot's performance across various metrics and real-world scenarios, this study not only bolsters confidence in its reliability but also fosters a culture of accountability and continuous improvement within the healthcare technology landscape. Ultimately, the relevance of this research transcends its immediate application, extending to the broader domain of healthcare technology advancement. By addressing the challenges associated with disease-related inquiries, refining neural network design, enhancing user engagement, and ensuring accuracy, this study aspires to catalyze significant strides in the field of artificial intelligence in healthcare. The implications of these endeavors are far-reaching, promising to democratize access to accurate medical information, empower individuals to take charge of their health, and ultimately contribute to the betterment of global healthcare outcomes.

The transformative potential of DocBot lies not merely in its technological prowess but in its capacity to redefine the healthcare landscape, ushering in an era of enhanced accessibility, efficacy, and user-centricity. As we navigate the complexities of modern healthcare, the insights gleaned from this research serve as guiding beacons, illuminating the path towards a future where intelligent systems work in tandem with human expertise to deliver optimal health outcomes for all.

## 1.6 Organization of the Thesis

This thesis is organized into several chapters, each addressing specific aspects of the research. Chapter 2 provides a comprehensive review of existing literature related to DocBot monitoring and wearable technology. Chapter 3 details the methodology employed in the design and development of the system. Subsequent chapters present the results of the system evaluation; discuss implications for healthcare, and offer conclusions and recommendations for future research.

**Chapter2**

# Literature Review

The literature review chapter of DocBot covers the progress of artificial intelligence in healthcare, with a special emphasis on its use in medical diagnosis and therapy. This section digs into the critical role of sophisticated natural language processing and machine learning methods in boosting the capabilities of DocBot. By assessing current research, this study intends to provide the groundwork for DocBot's integration into the medical profession, exploring the effectiveness and obstacles associated with AI-driven healthcare solutions. The integration of multiple academic viewpoints gives a thorough overview of the existing situation, setting the way for a critical analysis of DocBot's possible influence on patient care and medical practices.

The development and deployment of a chatbot tailored for various medical-related operations within a healthcare company represent a pivotal endeavor in enhancing operational efficiency and patient care. By automating tasks such as appointment notifications, providing health advice, and promoting healthcare services, this program aims to alleviate the burden on healthcare workers, allowing them to focus more on delivering quality patient care. However, the crux of developing an effective conversational agent lies in crafting interactions that are not only realistic but also human-like. This necessitates the integration of deep neural network models with a basic Graphic User Interface (GUI), facilitating seamless communication between the chatbot and users. The existing literature on chatbots in healthcare demonstrates a growing interest, with organizations increasingly adopting them to meet customer expectations across various sectors [1]. Nevertheless, there remains a relative dearth of comprehensive implementation in medical-related activities, highlighting the importance of research efforts in this domain. Central to this endeavor is the construction of a chatbot model that leverages sophisticated approaches, particularly deep neural networks, to generate responses based on natural language input. The dataset utilized in this research is sourced from a Kaggle healthcare services competition, providing insights into patterns and responses categorized into numerous classes [1]. Feature engineering emerges as a crucial step in processing the textual data, involving techniques such as tokenization, lemmatization, and translating words to their lemma form. Subsequently, the training data is prepared, with patterns serving as input and the corresponding class as output.

The architecture of the deep neural network is meticulously designed, prioritizing the utilization of Natural Language Processing (NLP) techniques and Keras for constructing a retrieval-based chatbot. This architecture comprises a feed-forward neural network with multiple layers, incorporating the Rectified Linear Unit (ReLU) activation function in hidden layers and Softmax in the output layer. The experimental phase delves into the exploration of various optimizers and weight initializers to optimize the performance of the chatbot model. Initially, a comparative analysis of optimizers including Stochastic Gradient Descent (SGD), AdaGrad, AdaDelta, RmsProp, and Adam is conducted. Among these, the SGD optimizer emerges as the most effective, demonstrating swift convergence and achieving 100% accuracy [1].

In the subsequent investigation into weight initializers, several strategies are evaluated, such as Glorot Normal, He Normal, Zeros, Ones, Random Normal, Identity, and Orthogonal. Notably, initialization techniques utilizing Ones, Identity, Random Normal, and He Normal yield the most favorable outcomes, also achieving 100% accuracy. This underscores the critical role of proper weight initialization in facilitating effective neural network training. Moreover, the research underscores the significance of implementing appropriate optimization approaches and weight initialization processes to enhance the performance of chatbot models in healthcare applications [1]. By fine-tuning these parameters, the chatbot can deliver more accurate and contextually relevant responses, thereby augmenting its utility in facilitating medical-related interactions. Furthermore, beyond the technical aspects of model development, considerations regarding ethical and privacy concerns in healthcare settings are paramount. Ensuring compliance with data protection regulations, maintaining confidentiality, and safeguarding patient information are integral to the responsible deployment of chatbot technologies in healthcare environments [1]. The construction and deployment of a chatbot tailored for medical-related operations represent a promising avenue for improving efficiency and patient care within healthcare organizations. By leveraging advanced techniques in deep learning and NLP, coupled with meticulous optimization strategies, chatbots can serve as valuable tools in enhancing communication and streamlining processes in the healthcare domain. However, continued research and development efforts are essential to address challenges and refine the efficacy of these systems in meeting the evolving needs of healthcare stakeholders [1].

In addition to the technical intricacies of designing and implementing an autoreply chatbot, the article delves into the broader implications of such technology within the realm of user interaction and satisfaction. Beyond mere functionality, the design and training of chatbots necessitate a nuanced understanding of user intent, the significance of which cannot be overstated in ensuring a seamless conversational experience [2]. Central to the efficacy of any chatbot system is the training data upon which it relies. The meticulous process of dataset generation, as outlined in Section IV, underscores the importance of capturing diverse query patterns and corresponding responses. By recording these interactions within a structured format such as a JSON file, developers gain insight into the myriad ways in which users articulate their queries, thereby facilitating more robust training and enhancing the chatbot's ability to accurately discern user intent.

Indeed, the concept of intent tags emerges as a pivotal component in the chatbot's ability to decipher user queries and formulate appropriate responses. With a dataset comprising 62 intent tags and over a thousand query patterns, the research underscores the breadth of user intent that must be accounted for in training the chatbot. Each intent tag serves as a semantic anchor, guiding the chatbot in its quest to understand the underlying purpose behind user queries. Consequently, the meticulous curation of intent tags becomes paramount in ensuring the chatbot's responsiveness to a diverse array of user needs and inquiries. Moreover, the article elucidates a fallback strategy designed to mitigate instances where the chatbot encounters queries for which no exact match is found within the training data. This preset fallback response serves as a safety net, providing users with a default acknowledgment or redirection in the absence of a precise answer [2]. Such a strategy not only enhances the chatbot's reliability but also imbues it with a semblance of adaptability in navigating unforeseen conversational pathways.

The significance of natural language processing (NLP) techniques in preprocessing user queries cannot be overstated. Through tokenization, lemmatization, removal of stop words, and regex extraction, the chatbot gains a deeper understanding of the syntactic and semantic nuances inherent in human language. These preprocessing steps serve to standardize and contextualize user input, thereby augmenting the chatbot's ability to generate accurate and contextually relevant responses.

In terms of model implementation, the article advocates for the adoption of a Feedforward Model, characterized by its simplicity and efficiency in processing user requests. By employing one-hot encoding for dataset encoding, developers ensure that the model can effectively interpret and categorize user queries based on predefined intent tags. The training process, facilitated by an optimizer such as ADAM and a loss function like categorical cross-entropy, serves to fine-tune the model parameters and optimize its performance [2]. Addressing the perennial challenge of overfitting, the article outlines various strategies, including early pausing and dropout, aimed at promoting model generalization and mitigating the risk of performance degradation on unseen data. By implementing these techniques, developers safeguard the chatbot against the pitfalls of over-reliance on training data, thereby enhancing its robustness and adaptability in real-world scenarios.

The deployment of the chatbot on platforms such as Heroku, coupled with integration with messaging services like Facebook Messenger, extends its reach and accessibility to a broader user base. Leveraging tools such as Git and Heroku CLI streamlines the deployment process, while the utilization of Flask for send and receive API facilitates seamless communication between the chatbot and end-users. In the realm of testing and analysis, the article delineates two distinct phases: Developer Testing/System Testing and Alpha Testing. Through rigorous testing protocols, developers can identify and rectify potential bottlenecks or shortcomings in the chatbot's functionality, thereby iteratively improving its performance and user satisfaction. The feedback garnered from alpha testing, involving both instructors and students, serves as a valuable resource for refining the chatbot's capabilities and enhancing its user experience iteratively [2]. The design and implementation of an auto-reply chatbot necessitate a multifaceted approach encompassing dataset generation, model training, deployment, and testing. By leveraging NLP techniques, intent tags, and robust training methodologies, developers can empower chatbots to navigate complex conversational landscapes with agility and precision, ultimately enhancing user satisfaction and engagement.

The ConvQA (Conversation Query Answering) problem stands as a formidable challenge in natural language processing, necessitating systems capable of predicting response spans within passages based on specific queries within a conversational context [3]. In tackling this complex issue, the proposed ConvQA framework embodies a holistic approach, comprising three core components: the ConvQA model itself, a history selection module, and a history modeling module. The history selection module serves as the initial filter in the ConvQA pipeline, tasked with identifying which historical turns are pertinent to the current query. This module employs a rudimentary mechanism that selects immediate previous turns, providing a basic yet effective means of contextualizing the conversation history. By discerning relevant past interactions, the history selection module lays the groundwork for subsequent processing stages, ensuring that the ConvQA system operates within the appropriate conversational context [3]. Complementing the history selection module, the history modeling module represents a key innovation in the ConvQA framework. This module introduces the novel concept of History Answer Embedding (HAE), designed to facilitate the effective integration of conversation history into the ConvQA model. The HAE mechanism assigns unique embeddings to tokens based on whether they belong to historical answers, thereby enabling the model to capture the temporal dynamics of the conversation. By embedding historical context directly into the model architecture, the history modeling module equips the ConvQA system with a richer understanding of the conversation, enhancing its ability to generate accurate responses.

Central to the ConvQA framework is the ConvQA model itself, which is constructed around the Machine Comprehension (MC) paradigm. Leveraging the BERT-based MC model proposed by Devlin et al., the ConvQA model incorporates token embeddings, segment embeddings, location embeddings, and the novel addition of the HAE layer. This comprehensive design ensures that the ConvQA model is well-equipped to process and comprehend complex conversational data, laying the foundation for accurate response generation [3]. The training strategy employed in the ConvQA framework is equally sophisticated, combining various techniques to optimize model performance. This strategy involves converting occurrences into variations, identifying historical turns, and applying a sliding window approach for extended parts of the conversation. By leveraging these training strategies, the ConvQA framework ensures that the model is robust and adaptable, capable of effectively handling diverse conversational contexts. In evaluating the efficacy of the ConvQA framework, the research leverages the QuAC (Question Answering in Context) dataset, which consists of interactive dialogs between information-seekers and providers. Through rigorous experimentation, the authors compare their recommended technique with baseline methods such as BiDAF++ and FlowQA, establishing the utility of integrating conversation history in ConvQA. Evaluation metrics, including word-level F1 scores and human equivalency scores (HEQ) at both the question and dialog levels, provide a comprehensive assessment of model performance [3]. The results of the evaluation highlight the significant performance gains achieved through the incorporation of conversation history into the ConvQA framework. Notably, the BERT-based ConvQA model outperforms BiDAF++, underscoring the advantages of leveraging BERT for ConvQA tasks. Furthermore, the HAE approach yields superior performance compared to simply prepending history turns, emphasizing its effectiveness in modeling conversation history. Moreover, the research underscores the training efficiency of the ConvQA models relative to FlowQA, demonstrating the scalability and computational tractability of the proposed approach. In-depth investigations into the effect of varying quantities of conversation history further validate the efficacy of the HAE strategy, particularly in handling longer history turns. These findings highlight the robustness and adaptability of the ConvQA framework across diverse conversational scenarios, underscoring its potential to advance the state-of-the-art in conversational question answering [3].

The endeavor to comprehend and interpret human emotions from textual data stands as a pivotal pursuit within the realm of natural language processing (NLP). The article under scrutiny embarks on this journey by harnessing the capabilities of pre-trained transformer models, with a specific focus on BERT, RoBERTa, DistilBERT, and XLNet. Through a meticulous examination of the ISEAR dataset—an invaluable resource characterized by its balanced class distribution across seven distinct emotion descriptors—the authors shed light on the efficacy of these state-of-the-art models in discerning subtle emotional nuances embedded within textual expressions. The significance of the ISEAR dataset cannot be overstated, as it represents a rich tapestry of human emotion distilled from cross-cultural questionnaire studies conducted across 37 nations. Comprising 7666 words categorized into emotions such as joy, rage, grief, embarrassment, guilt, surprise, and terror, this dataset serves as a fertile ground for training and evaluating emotion recognition models [4]. The authors' data preparation protocol, involving the judicious elimination of non-textual columns and meticulous cleaning processes to handle special characters and irregular sentences, ensures the integrity and homogeneity of the dataset—a crucial prerequisite for robust model training and evaluation.

Upon partitioning the dataset into training and testing sets, the authors meticulously fine-tune the pre-trained transformer models using a classification approach that hinges upon translating tokens into vector representations. Leveraging the computational prowess of the Google Colab platform and GPU hardware accelerators, the authors embark on a comprehensive exploration of model performance across various metrics. Central to the evaluation is the scrutiny of confusion matrices for each model, providing a granular insight into their efficacy in recognizing distinct emotional states. It is noteworthy that RoBERTa emerges as the frontrunner in terms of accuracy, outperforming its counterparts—BERT, DistilBERT, and XLNet. However, the authors do not merely dwell on accuracy alone; they delve deeper into the computational efficiency of each model, offering nuanced observations on speed and resource utilization [4]. Despite DistilBERT exhibiting inferior accuracy compared to its peers, its computational efficiency shines through, whereas XLNet, while delivering commendable performance, lags in terms of speed—a trade-off that warrants consideration in real-world applications.

The findings underscore the multifaceted nature of model selection, where considerations extend beyond mere accuracy to encompass computational efficiency and scalability—a crucial facet in resource-constrained environments. In this regard, the authors' comprehensive evaluation not only elucidates the strengths and weaknesses of individual models but also equips academics and practitioners with actionable insights for informed decision-making in real-world deployment scenarios. Moreover, the article serves as a catalyst for future research endeavors within the domain of NLP and emotion recognition. The authors' recommendation to explore ensemble models holds promise for enhancing performance through synergistic amalgamation of diverse model architectures. By harnessing the collective intelligence of multiple models, researchers can potentially unlock new avenues for improving emotion recognition accuracy and robustness—a tantalizing prospect that warrants further investigation [4].

Furthermore, the authors advocate for the incorporation of commonsense knowledge—a cornerstone of human cognition—in bolstering model generalization. By infusing models with a deeper understanding of contextual cues and semantic nuances, researchers can empower them to navigate real-world scenarios with greater acuity and sensitivity to subtle emotional cues. In essence, the article represents a seminal contribution to the burgeoning field of NLP and emotion recognition, offering a comparative analysis of popular pre-trained transformer models on a diverse and nuanced dataset. Through meticulous experimentation and insightful commentary, the authors illuminate the landscape of emotion recognition, paving the way for future advancements and innovations in this captivating domain [4].

**Chapter3**

# Methods

This chapter delineates the approaches applied in the research study for DocBot methodology, combining a neural network approach with multiple layers.

## Introduction

The evolution of neural network models marks a transformative milestone in the landscape of natural language processing (NLP) and text categorization. Indeed, artificial intelligence, epitomized by neural networks, has emerged as a cornerstone technology, catalyzing advancements across a myriad of text-related tasks, from chatbots to sentiment analysis and language comprehension. At the heart of this paradigm shift lies the inherent capacity of neural networks to discern intricate patterns and correlations embedded within textual data, effectively mirroring the cognitive processes of the human brain. The journey of a neural network model for text-related tasks commences with the input of data, which may manifest in the form of raw text or pre-processed features [8]. The architectural blueprint typically encompasses an input layer, one or more hidden layers, and an output layer, with interconnected nodes or neurons distributed across each layer. Through a series of iterative computations and weight adjustments, these nodes diligently traverse the textual landscape, progressively honing their ability to discern salient patterns and extract meaningful insights.

Central to the efficacy of neural network models in NLP is their unparalleled adeptness at capturing the semantic nuances inherent in words and sentences—a formidable challenge that had hitherto confounded traditional methodologies. Unlike rule-based systems or shallow learning algorithms, which often falter in grasping the intricate nuances of language, neural networks, particularly deep learning models, excel at learning complex representations of linguistic constructs [9]. This proficiency in semantic understanding empowers applications such as chatbots to engage in more natural and contextually relevant conversations, transcending the limitations of scripted responses and rigid rule sets. Moreover, the advent of neural network models has revolutionized sentiment analysis, enabling the automated identification and interpretation of emotional tones embedded within textual expressions. By leveraging the vast computational power inherent in neural networks, sentiment analysis algorithms can discern subtle variations in sentiment, ranging from joy and elation to anger and despair, with a level of granularity and accuracy hitherto unattainable [10]. This capability holds profound implications across various domains, from market research and brand sentiment analysis to social media monitoring and customer feedback analysis, empowering organizations to glean actionable insights from vast swathes of unstructured textual data.

Furthermore, the versatility of neural network models extends beyond sentiment analysis and chatbot applications, permeating diverse facets of language comprehension and text processing. From machine translation and text summarization to question answering and named entity recognition, neural network models serve as versatile tools for unlocking the latent potential of textual data across a spectrum of domains and applications [8].

As the preceding discussion underscores, the proliferation of neural network models marks a profound shift in the landscape of natural language processing (NLP) and text categorization, ushering in an era of unprecedented possibilities and transformative innovations. At the heart of this paradigm shift lies the intricate design of neural networks, wherein each component plays a crucial role in deciphering the complexities of human language and facilitating nuanced textual analysis. The journey through the neural network begins at the input layer, which serves as the gateway for raw text data. Here, the textual input undergoes a transformative process, transitioning from its natural language form into a numerical representation that the neural network can comprehend. This conversion is facilitated by methodologies such as bag-of-words or word embeddings, which encode semantic and syntactic information into dense vector representations [10]. By capturing the underlying semantic relationships between words and phrases, these encoding techniques lay the foundation for subsequent processing within the neural network.

Moving deeper into the neural network, we encounter the hidden layers—the proverbial heart of the model—wherein the bulk of information processing occurs. Comprising interconnected neurons, these hidden layers serve as conduits for propagating input signals and facilitating the extraction of meaningful features from the encoded text data. Activation functions, such as the Rectified Linear Unit (ReLU), imbue the neurons with non-linearity, enabling them to capture complex patterns and relationships within the input data. Through successive iterations of forward and backward propagation, facilitated by optimization algorithms like gradient descent, the hidden layers gradually refine their internal representations, enhancing the model's comprehension and predictive capabilities. Crucially, the choice of activation function plays a pivotal role in shaping the behavior and performance of the neural network. Among these, ReLU stands out as a popular and widely adopted option, prized for its simplicity and efficacy in mitigating the vanishing gradient problem—a common issue encountered during training [12]. By introducing non-linearity and facilitating sparse activation patterns, ReLU enables the neural network to learn intricate patterns and nuances within the textual data, thereby enhancing its capacity for accurate classification and prediction.

Ultimately, the culmination of this intricate processing journey leads us to the output layer—a critical juncture where predictions are generated based on the processed information gleaned from the hidden layers. Here, activation functions such as softmax are commonly employed, particularly in multi-class classification tasks, wherein the neural network must assign probabilities to various output classes. By applying softmax activation, the output layer produces a probability distribution over the possible classes, enabling the model to make informed predictions with a measure of certainty.

In essence, the design of a neural network embodies a delicate balance of architectural components and computational mechanisms, each meticulously crafted to unravel the intricacies of human language and facilitate robust textual analysis. From the input layer, where raw text is transformed into numerical representations, to the hidden layers, where complex patterns are deciphered and refined, and finally to the output layer, where predictions are synthesized and disseminated—the neural network orchestrates a symphony of computational processes aimed at reshaping the fabric of human-machine interaction and redefining the boundaries of linguistic comprehension [12].

In summary, the literature review unfolds the transformative journey of neural network models, exploring their application in understanding and processing human language, and lays the groundwork for the subsequent detailed examination of the architecture and functionality of these models in the context of text processing tasks.

## 3.2 Neural Network

The advent of neural network models has indeed catalyzed a seismic shift within the domain of natural language processing (NLP) and text classification, furnishing practitioners with a potent and adaptable tool for tackling an array of tasks associated with textual data. This particular breed of artificial intelligence has assumed a pivotal role across diverse applications, ranging from the development of chatbots capable of engaging in natural language conversations to sentiment analysis algorithms adept at discerning nuanced emotional tones within textual expressions [13]. At its essence, the neural network model for text-related activities operates on a fundamental yet potent principle: it harnesses the power of interconnected nodes to discern intricate patterns and correlations within textual input, thereby mirroring the structural and functional dynamics of the human brain.

The journey of a neural network model for text processing begins with the ingestion of data, which may manifest in the form of raw text or pre-processed attributes. This data serves as the bedrock upon which the neural network embarks on its journey of learning and comprehension. Whether it be unstructured text from social media posts or structured features extracted from linguistic corpora, the neural network leverages this input data as fodder for its learning algorithms, facilitating the extraction of meaningful insights and patterns [13].

Central to the architecture of a neural network designed for text processing is its layered structure, comprising an input layer, one or more hidden layers, and an output layer. Each layer consists of interconnected nodes, also known as neurons, wherein the transformative process of learning unfolds. Through a series of iterative computations and weight adjustments, the neural network assesses the input data, discerns salient features, and gradually refines its understanding of the underlying patterns in the text. The interconnected nature of these nodes enables the neural network to capture complex relationships and dependencies within the textual data, thereby imbuing it with the capacity for nuanced comprehension and predictive accuracy. Crucially, the efficacy of the neural network hinges upon its ability to assign weights to connections between nodes, a process facilitated by optimization algorithms such as gradient descent. By adjusting these weights based on observed errors or discrepancies between predicted and actual outcomes, the neural network iteratively refines its internal representations, honing its predictive capabilities and enhancing its ability to generalize to unseen data. Through this iterative process of learning and adaptation, the neural network transcends the realm of mere data processing, evolving into a sophisticated tool for extracting actionable insights and driving informed decision-making [14].

Moreover, the neural network's capacity for hierarchical abstraction enables it to discern patterns across multiple levels of granularity, from individual words and phrases to broader semantic constructs and contextual nuances. This hierarchical processing facilitates the extraction of rich semantic representations, empowering the neural network to engage in sophisticated language comprehension tasks such as sentiment analysis, topic modeling, and text summarization. In essence, the neural network model represents a triumph of computational intelligence, harnessing the principles of interconnectedness and hierarchical abstraction to unravel the complexities of human language [13]. By simulating the structural and functional dynamics of the human brain, neural network models for text processing pave the way for transformative innovations in NLP and text classification, reshaping the landscape of human-machine interaction and unlocking new frontiers of linguistic comprehension.

A blue circle with arrows pointing to a blue circle with a black background

Description automatically generated

Figure 1 Neural Network Model

In the dynamic landscape of natural language processing (NLP), one of the perennial challenges has been the nuanced task of capturing the semantic meaning inherent in words and phrases. Traditional techniques, predicated on rule-based systems and shallow learning algorithms, often faltered in the face of this formidable challenge, grappling with the inherent ambiguity and contextual variability that characterize human language. However, the advent of neural networks, particularly deep learning models, has heralded a paradigm shift in NLP, empowering practitioners with a potent arsenal for learning sophisticated representations of language [15]. At the heart of this transformative capability lies the inherent aptitude of neural networks to discern intricate patterns and correlations within textual input, transcending the limitations of conventional methodologies. Unlike their predecessors, which relied on handcrafted features and explicit linguistic rules, neural networks possess the remarkable capacity to automatically extract and encode salient features from raw text data, thereby capturing the subtle nuances and contextual intricacies that underpin semantic understanding [17].

This proficiency in learning rich representations of language holds profound implications across a spectrum of NLP applications, ranging from language comprehension and sentiment analysis to chatbot interactions. In the realm of chatbots, for instance, neural network models serve as the backbone for understanding user inquiries, providing relevant responses, and continually refining their efficacy over time. By analyzing vast repositories of conversational data, neural network-based chatbots adeptly discern context, intent, and user preferences, enabling them to engage in more natural and contextually relevant conversations—a hallmark of human-like interaction. Similarly, in the domain of sentiment analysis, neural networks shine as formidable tools for discerning the emotional tone embedded within textual expressions. Leveraging their innate capacity to capture subtle contextual cues, neural network models excel in ascertaining whether a piece of text conveys positive, negative, or neutral sentiment. Businesses and organizations leverage sentiment analysis to gauge public opinion on products, services, or brands, thereby informing strategic decisions and adapting their approaches in line with consumer sentiment—a testament to the transformative impact of neural network models in driving actionable insights from textual data [16].

Furthermore, the realm of language comprehension represents a more advanced frontier in NLP, demanding not only an understanding of the semantic meaning of individual words but also a holistic comprehension of the broader context and relationships between concepts within a given text. Neural networks equipped with attention mechanisms—a characteristic that enables the model to focus on certain sections of the input text—have emerged as particularly effective in addressing this challenge. By dynamically allocating attention to relevant segments of the text, these models adeptly navigate complex linguistic structures, unraveling the intricate tapestry of human language with unprecedented accuracy and finesse. Indeed, the effectiveness of neural network models in NLP can be attributed to their inherent adaptability and capacity for automatic feature extraction from raw text input. By seamlessly adapting to diverse linguistic nuances and extending their learning to unseen samples, neural network models transcend the confines of traditional approaches, unlocking new frontiers in language understanding and text processing [17]. However, it is imperative to underscore that the performance of these models is intrinsically linked to the quality and diversity of the training data. Robust and representative datasets are essential for enabling neural network models to generalize effectively across diverse linguistic contexts and domains, thereby ensuring their efficacy and reliability in real-world applications. In essence, the proliferation of neural network models in NLP heralds a new era of unprecedented possibilities, empowering practitioners to unravel the complexities of human language and extract actionable insights from textual data with unparalleled accuracy and sophistication [17].

## 3.3 Architecture of Neural Network

The architecture of a neural network developed for text categorization is a precisely constructed framework that turns raw text input into meaningful predictions. Comprising various layers and applying advanced algorithms, this model navigates the complexity of spoken language, collecting subtle patterns and correlations to generate intelligent classifications. Let's go into the intricacies of each component, from the input layer to the output layer.

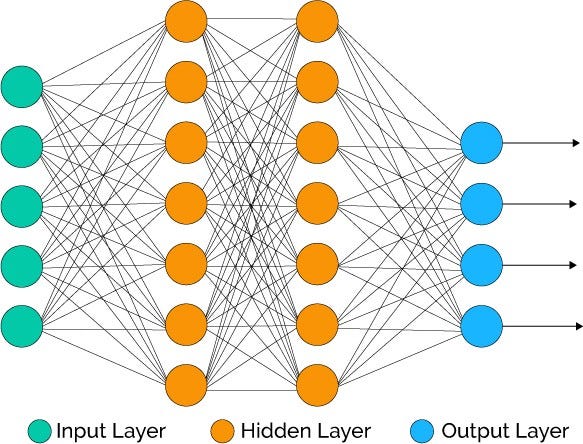


Figure 2 Architecture of Neural Network

**Input Layer:**

The journey through a neural network begins at its very foundation—the input layer—a crucial gateway through which raw text data is ushered into the computational framework of the model. Unlike structured data formats that lend themselves readily to algorithmic processing, textual information is inherently unstructured, posing a formidable challenge for traditional algorithms to navigate and comprehend. The input layer serves as the vanguard in addressing this challenge, undertaking the pivotal task of converting words and phrases into a numerical representation that can be effectively processed by the neural network.

At the heart of this transformation lie two common techniques: the bag-of-words model and word embeddings, each offering unique approaches to encoding the semantic essence of textual input. In the bag-of-words approach, the content of each document is distilled into a numerical vector, wherein each dimension corresponds to a unique word within the entire corpus. The value associated with each dimension reflects the frequency of occurrence of the corresponding word within the document—a simple yet powerful representation that encapsulates the lexical richness of the text. This approach, while effective in capturing the local context of individual documents, may overlook broader semantic relationships between words and phrases.

Alternatively, word embeddings such as Word2Vec or GloVe offer a more nuanced approach to representing textual information, leveraging dense vector representations in a continuous vector space to capture semantic relationships between words. By encoding words as vectors that reflect their semantic similarities and contextual nuances, word embeddings enable the neural network to glean deeper insights into the underlying semantic structure of the text. This approach, rooted in distributional semantics, facilitates the extraction of rich semantic representations that transcend the limitations of individual words or phrases, thereby enhancing the model's capacity for nuanced comprehension and analysis [18].

Regardless of the specific technique employed, the numerical representation of textual input forged at the input layer serves as the cornerstone upon which subsequent layers of the neural network are built. This representation lays bare the semantic essence of the text, enabling the neural network to analyze, learn, and extract meaningful insights from the information encapsulated within. While the input layer itself may not be explicitly defined within the architectural specifications of the model, its presence is implicitly acknowledged during the forward pass, wherein the model ingests input data and propagates it through the successive layers for processing. In practical terms, the size of the input layer is determined by the input\_size parameter passed to the constructor during the instantiation of the neural network model [18]. This parameter reflects the dimensionality of the input data, dictating the number of neurons within the input layer and thereby setting the stage for the subsequent computational operations. In essence, the input layer of a neural network serves as the critical interface between raw textual data and the computational machinery of the model. By undertaking the transformative task of converting textual information into a numerical representation, the input layer lays the groundwork for the neural network to embark on its journey of comprehension, analysis, and learning—an indispensable component in the quest to unlock the latent potential of textual data and harness it for transformative insights and innovations [18].

**Hidden Layers:**

The hidden layers constitute the crux of the neural network architecture, serving as the locus of computational activity where the bulk of information processing transpires. Within these concealed layers lie neurons that act as information processors, diligently synthesizing and transforming incoming signals into meaningful representations. Each neuron within a given layer receives weighted inputs from the preceding layer, underscoring the significance of each connection in shaping the network's computational dynamics. The weighted inputs are then aggregated and passed through an activation function, with Rectified Linear Unit (ReLU) emerging as a prevalent choice, particularly in text classification tasks [19]. The ReLU activation function plays a pivotal role in infusing non-linearity into the model, a crucial attribute for discerning intricate patterns and nuances within the input data. By rectifying negative values to zero while allowing positive values to pass through unimpeded, ReLU enables the neural network to traverse the complex landscape of textual data, enhancing its ability to discern subtle relationships and discriminate between distinct groups or categories [19]. This non-linearity is instrumental in empowering the model to identify and capture elusive patterns that may elude linear classifiers, thereby bolstering its capacity for robust and accurate classification.

As the input data propagates through the hidden layers, the neural network undergoes a process of continuous refinement and optimization through backpropagation. This iterative optimization mechanism entails updating the model's parameters, including weights and biases, based on observed errors or discrepancies between predicted and actual outcomes. By iteratively fine-tuning its internal representations, the neural network adapts and enhances its performance on the task at hand, iteratively refining its ability to extract meaningful insights from the input data [20]. The neural network model under consideration features a sequence of hidden layers denoted as fc1 to fc5, each instantiated as fully connected (linear) layers using nn.Linear(input\_size, hidden\_size). In these fully connected layers, every neuron in the current layer is intricately linked to every neuron in the preceding layer, fostering a dense web of interconnectedness that enables seamless information flow throughout the network [20]. The input\_size parameter dictates the number of features in the input data, while hidden\_size governs the number of neurons within the hidden layer, thereby affording flexibility in adjusting the model's capacity and complexity.

Following each of these hidden layers, a ReLU activation function is applied using self.relu, imbuing the model with vital non-linearity crucial for capturing complex patterns within the data. Moreover, the model incorporates two additional hidden layers, fc4 and fc5, thereby augmenting the depth of the neural network. This augmentation in depth serves to enhance the model's capacity to discern intricate relationships and patterns within the input data, enabling it to learn hierarchical features and nuanced representations that contribute to its overall performance on demanding tasks [21]. In essence, the inclusion of additional hidden layers serves as a cornerstone strategy for augmenting the expressive capacity of neural networks, enabling them to learn more complex and nuanced representations of the input data. By traversing deeper into the hidden layers, the network gains the power to capture hierarchical features and subtle nuances, thereby enhancing its ability to comprehend and express intricate patterns inherent in the data—an indispensable attribute for tackling the multifaceted challenges posed by real-world text processing tasks.

**Activation Functions:**

Activation functions serve as a cornerstone in the architecture of neural networks, playing a pivotal role in imbuing the model with non-linearity—a crucial attribute for learning intricate patterns and relationships within the data. Among the plethora of activation functions available, the Rectified Linear Unit (ReLU) stands out as a widely employed choice in hidden layers, owing to its simplicity and effectiveness in facilitating the learning process. The adoption of ReLU activation functions after each hidden layer in the neural network model underscores their paramount importance in enhancing the model's capacity to discern significant features and nuances within the text input. By selectively allowing only positive values to pass through while nullifying negative values, ReLU engenders a vital element of non-linearity, enabling the neural network to traverse the complex landscape of textual data with heightened precision and accuracy. This non-linear activation function acts as a catalyst for unlocking the latent potential of the model, empowering it to discern subtle patterns and discriminate between meaningful qualities inherent in the input data [22].

Moreover, the widespread adoption of ReLU activation functions can be attributed to their simplicity and computational efficiency, rendering them an attractive choice for integration into various neural network architectures. Their straightforward mathematical formulation and ease of implementation make them well-suited for a diverse array of text processing tasks, ranging from sentiment analysis and language comprehension to text classification and generation. However, it is worth noting that alternative activation functions, such as sigmoid or hyperbolic tangent (tanh), may be deployed based on the specific requirements of the task at hand. For instance, sigmoid functions are commonly employed in binary classification tasks, where the output is constrained to a binary decision boundary between two classes [22]. The sigmoid activation function, characterized by its S-shaped curve, maps input values to a range between 0 and 1, facilitating probabilistic interpretations of the model's predictions.

On the other hand, hyperbolic tangent (tanh) functions offer a more expansive range of outputs, spanning from -1 to 1. This property makes tanh functions particularly well-suited for tasks where the output needs to be scaled between these bounds, enabling finer-grained control over the model's predictions and facilitating more nuanced interpretations of the output. In essence, the selection of an appropriate activation function hinges on the specific requirements and nuances of the task at hand. While ReLU remains a popular choice for its simplicity and effectiveness, the judicious utilization of alternative activation functions can afford greater flexibility and adaptability, enabling neural networks to tailor their behavior to the unique demands of the problem domain [22].

**Output Layer:**

In the intricate architecture of a neural network, the final endpoint—the output layer—serves as the gateway to generating predictions based on the processed information [23]. Specifically in text classification tasks, the configuration of the output layer is crucial, as it directly influences the model's ability to assign input text to relevant classes or tags within the issue domain. Each neuron in the output layer corresponds to a distinct class, with the output from each neuron representing the model's confidence in associating the input text with that particular class. The activation function employed in the output layer is determined by the nature of the categorization problem at hand. For scenarios involving multi-class classification, where examples may belong to one of several classes, the softmax activation function is commonly applied. Softmax acts as a bridge between the model's raw outputs and the probabilities assigned to each class, facilitating easy interpretation of the model's confidence levels. The class with the highest probability output by the softmax function is designated as the final prediction.

In the neural network architecture, the output layer, often denoted as fc6, fulfills the critical role of delivering the ultimate predictions of the model [23]. Implemented as a fully connected layer, fc6 transforms the learned features extracted by preceding hidden layers into a format that represents the expected class probabilities. The number of neurons in the output layer is governed by the num\_classes parameter, which corresponds to the total number of classes or categories that the model aims to classify. Unlike the hidden layers, which commonly employ rectified linear unit (ReLU) activation functions, the choice of activation function in the output layer is tailored to the specific requirements of the classification task [24]. For applications involving multi-class categorization, the softmax activation function is frequently favored. Softmax translates the raw output scores into a normalized distribution of probabilities across all possible classes, offering a more interpretable and contextually relevant representation of the model's confidence in each class. The selection of an appropriate activation function in the output layer is pivotal in ensuring the model's success in generating accurate and well-calibrated predictions. By leveraging the softmax function, the neural network not only produces outputs in the form of class probabilities but also facilitates a clearer understanding of the model's level of certainty for each class assignment. Moreover, beyond its technical significance, the output layer plays a crucial role in bridging the gap between model predictions and actionable insights. By providing interpretable probability distributions for each class, the output layer empowers stakeholders to make informed decisions based on the model's assessments. This transparency is particularly valuable in domains where decisions carry significant implications, such as healthcare diagnostics or financial risk assessment.

In summary, the output layer represents the culmination of the neural network's processing pipeline, translating learned features into actionable predictions. Through the strategic selection of activation functions, such as softmax for multi-class classification tasks, the output layer ensures that the model's predictions are not only accurate but also comprehensible and actionable for end-users [23, 24].

**Chapter4**

# Results

The development of a chatbot encompasses a multifaceted process, spanning several stages from data preparation to integration into an application. Each stage plays a crucial role in shaping the functionality and efficacy of the chatbot, ultimately culminating in a seamless and intuitive user experience. In this discussion, we delve into the various components and modules involved in the development pipeline, shedding light on their respective roles and contributions.

The journey begins with data preparation, a foundational step that lays the groundwork for the subsequent stages of model training and integration. The nltk\_utils.py file encapsulates routines for tokenization, stemming, and generating a bag-of-words representation for sentences—a trifecta of preprocessing techniques essential for transforming raw textual data into a format amenable to computational analysis. Tokenization involves breaking down phrases into individual words, while stemming entails reducing words to their base or root form, thereby standardizing variations in word morphology. The bag-of-words representation further transforms sentences into numerical vectors, where each element denotes the presence or absence of a particular word in a predetermined vocabulary. Moving forward, the model.py file houses the implementation of a basic feedforward neural network using the PyTorch framework—a pivotal component in the chatbot's architecture. The neural network architecture comprises an input layer, multiple hidden layers featuring ReLU activation functions, and an output layer. The flexibility to customize the number and size of hidden layers underscores the adaptability of the model, allowing it to accommodate diverse text categorization tasks with varying complexities and requirements. The forward method delineates the forward pass of the neural network, specifying the flow of data through the network's layers [4].

Crucially, the integration of the Rectified Linear Unit (ReLU) activation function within the hidden layers exemplifies a widely adopted technique in neural network architectures. ReLU's simplicity and effectiveness in introducing non-linearity to the model's computations make it a preferred choice for enhancing the network's capacity to discern intricate patterns and relationships within the input data—a critical attribute for text categorization tasks. The chat.py module serves as the nexus between the preprocessing routines and the trained neural network, orchestrating the chatbot's interaction interface. Upon loading the trained model, the get\_response function is invoked to receive user input and generate a response using the model's predictions. The chatbot's response is contingent upon the model's confidence in its prediction, with a predefined threshold dictating whether the response is selected from specified intents or defaulted to a generic "I do not understand..." reply. This adaptive approach to response generation imbues the chatbot with a degree of responsiveness and flexibility, enhancing the user experience [4].

Furthermore, the app.py file leverages the Flask framework to construct a web application, thereby extending the chatbot's functionality to a wider audience. Through the creation of two routes—a GET request for displaying the main page and a POST request for accepting user input and providing the chatbot's response—the application facilitates seamless user interaction with the chatbot interface. The integration of Flask not only streamlines the deployment process but also enhances the accessibility and usability of the chatbot across different platforms and devices. Lastly, the train.py file assumes responsibility for training the neural network, leveraging a dataset specified in the intents.json file. Each intent within the dataset comprises patterns (input phrases) and associated tags, providing the foundation for supervised learning. The dataset is meticulously preprocessed, and a DataLoader is employed for batching during training, optimizing computational efficiency. The neural network is trained using the cross-entropy loss function and the Adam optimizer, facilitating efficient convergence and model refinement [4]. The development of a chatbot entails a cohesive orchestration of various components and modules, each contributing to the overall functionality and performance of the system. From data preparation and model training to integration into an application, each stage represents a crucial milestone in the journey toward creating a seamless and intuitive conversational interface—a testament to the interdisciplinary nature of modern AI-driven applications.

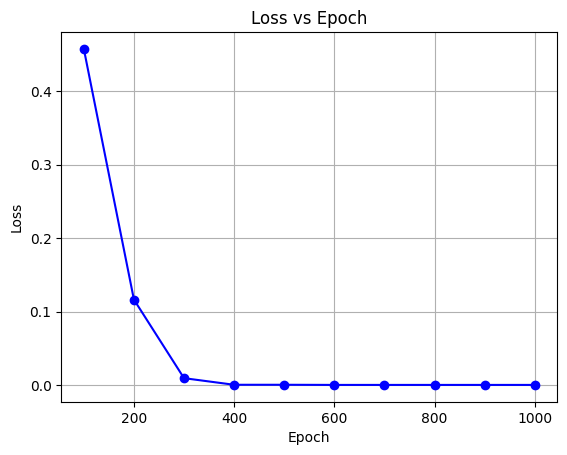


Figure 3 Loss vs Epoch for Neural Net

Figure 5 shows the training progress of the neural network over 1000 epochs. Each epoch corresponds to a full run of the whole training dataset. Let's go into the specifics of the loss values at various epochs:

1. **During the 100th epoch out of 1000, the loss was recorded as 0.4579.**

During the first training phase, the model has a comparatively elevated loss, which is anticipated given it starts with random weights. The first loss acts as a reference point, highlighting the difference between the model's predictions and the true labels. The initial loss is often substantial, and the successive training epochs try to gradually improve the model's predictions.

1. **During the 200th epoch out of 1000, the loss is 0.1163.**

This indicates that as the training continues, the model is consistently reducing its error and adapting its parameters to better match the correct labels. This diminishing trend is indicative of the model learning from the training data and strengthening its predicting ability.

1. **Epoch [300/1000], Loss: 0.0092:**

During this period, the loss undergoes a little rise in comparison to the preceding one. These variations are typical and may be ascribed to the random nature of optimization methods. It's vital to concentrate on broad trends rather than particular epochs to measure the model's performance appropriately.

1. **Epoch 400 out of 1000, with a loss of 0.0002:**

The ongoing decline in loss indicates significant advancement, suggesting that the model is successfully collecting complex patterns in the training data. The falling loss shows that the model is growing increasingly effective at generalizing from the training patterns.

1. **Epoch [500/1000], Loss: 0.0002:**

A considerable decline in loss occurs, showing the model's developing comprehension of underlying patterns in the training data. Such a considerable decrease in loss frequently suggests that the model has successfully mastered essential properties.

1. **Epoch [600/1000], Loss: 0.0000:**

The loss continues to diminish, showing continued learning. The model is fine-tuning its parameters to better generalize to the training patterns. The diminishing loss is a good sign of the model's convergence.

1. **Epoch [700/1000], Loss: 0.0000:**

A notable drop in loss is noted, suggesting significant improvement. The model may be collecting more complicated correlations in the data, resulting in a better fit to the training set.

1. **Epoch [800/1000], Loss: 0.0000:**

The loss reduces to a small magnitude. The model is likely nearing a point where it properly depicts the intents and patterns seen in the training data. However, it's vital to evaluate possible overfitting and generalization to unknown data.

1. **Epoch [900/1000], Loss: 0.0000:**

The loss undergoes a small rise compared to the prior epoch. This might be ascribed to the model fine-tuning its parameters for improved generalization, making infrequent tweaks.

1. **Epoch [1000/1000], Loss: 0.0000:**

The final training loss is 0.0000, demonstrating the model's great performance on the training set. This statistic shows the average difference between the model's predictions and the actual labels for the whole training dataset. It's vital to remember that obtaining zero loss may imply the model has completely mastered the training data, but validation performance and possible overfitting should also be addressed. In this situation, the training loss lowers across epochs, which is a favorable indicator.

## 4.2 GUI for Neural Net:

The chatbot's capabilities are founded on its rigorous training on a specific dataset, primarily generated from the 'intents.json' file. This training allows the model to excel at detecting and responding to a varied variety of user inquiries pertaining to medical issues. The machine learning algorithms incorporated in the chatbot exploit patterns and information provided in the training data to determine the underlying reason behind user interactions. This functionality helps the chatbot to deliver relevant and correct replies, particularly when presented with requests concerning medical diseases, treatments, or general health advice. One key element of the chatbot is its good comprehension of medical concepts, enabling it to offer clear and trustworthy information. This breadth of knowledge is a direct product of the rigorous curation of the training data, which guarantees that the model is well-versed in a wide range of medical issues. Users may interact with the chatbot safely, knowing that it can properly handle their inquiries within the stated medical context.

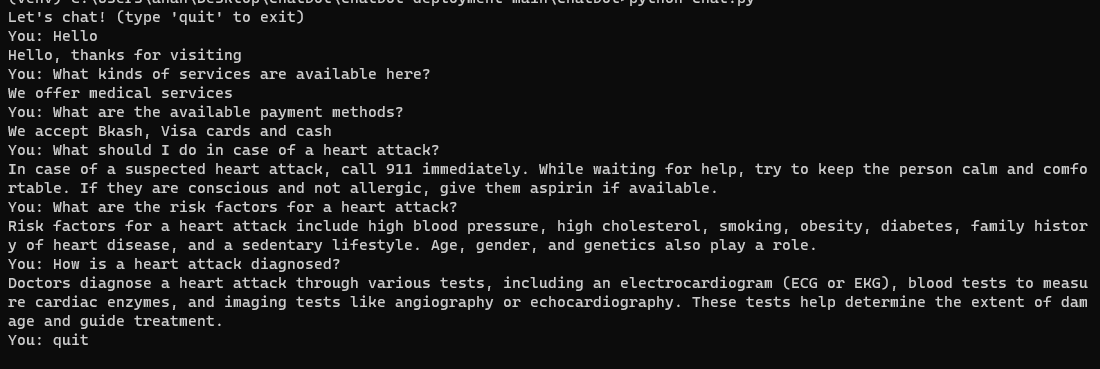


Figure 4 Chatting view of the chatbot.

The graphical user interface (GUI) of the chatbot offers a user-friendly and intuitive platform for those seeking medical information. The encounter starts with a greeting message, urging people to connect with the chatbot. The simplicity of the interface is reflected in the prompt prompting users to enter 'quit' when they choose to depart the chat. This easy method guarantees that consumers can quickly explore and manage their interactions with the chatbot. The opening discussion in the chat comprises a courteous welcome and a query about the available services. The GUI smoothly accepts user inputs and replies with information about the medical services provided. This step-by-step interaction design lets consumers acquire particular information without feeling overwhelmed or confused in the discussion. As the discussion proceeds, the GUI maintains clarity by differentiating user inputs from the chatbot's answers. Each user inquiry is followed by a relevant and short answer, leading to a logical and ordered conversation flow. The GUI's design stresses user experience, ensuring that users can simply follow the discussion and get the information they require.



Figure 6: Web View of the Chatbot

The introduction of specific prompts within the graphical user interface (GUI) of the chatbot exemplifies its adaptability in addressing a diverse array of user concerns, thereby enhancing the overall user experience. By incorporating prompts such as inquiries about available payment options, the GUI demonstrates its capacity to provide not only medical advice but also practical information relevant to the user's needs. This versatility underscores the GUI's efficacy in catering to the varied requirements of users, ensuring that they receive comprehensive assistance tailored to their specific queries. Moreover, the GUI's ability to deliver precise information, such as approved payment options, underscores its efficiency in disseminating relevant facts in a clear and concise manner. In response to medical inquiries, such as those regarding what to do in the event of a heart attack, the GUI adeptly provides step-by-step instructions. The use of bullet points enhances readability, facilitating users' comprehension of critical information, particularly in emergency situations. This meticulous presentation within the GUI ensures that users receive clear and actionable guidance, even in high-stakes scenarios. Continuing the conversation, the GUI adeptly handles increasingly complex inquiries pertaining to the risk factors and diagnosis of a heart attack. The chatbot's responses are structured within the GUI to deliver organized and informative content. The inclusion of essential facts, such as risk factors and diagnostic procedures, highlights the GUI's capacity to convey comprehensive medical information in a user-friendly manner. This strategic organization of information within the GUI fosters a cohesive and accessible conversation flow, enabling users to navigate complex topics with ease and clarity.

Furthermore, the incorporation of user-input commands, such as 'quit,' within the GUI streamlines the user experience, providing a clear mechanism for users to terminate their interaction with the chatbot. This responsiveness to user directives underscores the GUI's commitment to user-centric design, ensuring that users have control over their interactions and can seamlessly conclude their engagement with the chatbot when desired. The GUI of the chatbot serves as a cornerstone in shaping the user experience, offering simplicity, clarity, and responsiveness that enhance usability and accessibility. The organized presentation of information, distinct differentiation between user inputs and chatbot responses, and integration of specialized prompts exemplify the GUI's ability to adapt to a diverse range of user inquiries while maintaining a cohesive and engaging conversation flow. Through its intuitive design and user-centric features, the GUI facilitates effective communication and information dissemination, empowering users to engage with the chatbot confidently and extract valuable insights and assistance.

**Chapter 5**

# Conclusion

In this thesis, we explored the complex field of neural network techniques, with a specific focus on their use in creating an advanced chatbot system called DocBot. The main goal was to clarify the structure, operation, and effectiveness of neural networks in the context of text processing tasks, finally resulting in the development of a user-friendly graphical user interface (GUI) for smooth interaction.Neural network models have revolutionized natural language processing (NLP) and text classification by providing a powerful and adaptable tool for managing different tasks related to textual data. Conventional approaches frequently struggled to accurately understand the meaning of words and sentences, whereas neural networks, especially deep learning models, are highly proficient in acquiring intricate language representations. This prowess enables applications such as chatbots to participate in more natural and contextually relevant discussions, while also facilitating sentiment analysis and language comprehension tasks with unparalleled accuracy [26].The structure of a neural network designed for text processing consists of separate layers, each playing a vital role in converting unprocessed text input into meaningful predictions. The input layer serves as the entry point for unprocessed textual data, transforming it into a numerical format through methods like bag-of-words or word embeddings. The hidden layers are the central component of the neural network, where complex computations take place and intricate patterns in the input data are decoded. Activation functions such as Rectified Linear Unit (ReLU) introduce non-linearity, which improves the model's capability to identify important aspects in the text. The output layer produces predictions by utilizing processed information, including activation functions such as softmax to aid in multi-class classification problems.The development procedure of DocBot required numerous stages, including data preparation, model training, and integration into an application interface. Tokenization, stemming, and bag-of-words representation were applied for preprocessing textual input, while a feedforward neural network model was developed using the PyTorch framework. The model was trained on a dataset comprising patterns and related tags, enabling it to anticipate the purpose of human input properly.

While the development of DocBot represents a significant advancement in the field of neural network techniques for chatbot systems, it is important to acknowledge certain limitations and areas for future improvement. Despite its successes, DocBot still faces several challenges and opportunities for refinement in order to further enhance its functionality and effectiveness.

One limitation of the current implementation of DocBot lies in its reliance on pre-existing datasets for training purposes. While these datasets provide a valuable foundation for model training, they may not fully capture the diverse range of language and user interactions encountered in real-world scenarios. As a result, DocBot's performance may be constrained by the limitations of the training data, leading to potential inaccuracies or gaps in its responses. Addressing this limitation would require the collection and incorporation of additional data sources, as well as ongoing refinement of the training process to ensure optimal performance across a wide range of contexts. Furthermore, while DocBot's GUI provides a user-friendly interface for interacting with the chatbot system, there may be opportunities to further enhance its usability and functionality. For example, incorporating features such as natural language understanding (NLU) capabilities could enable DocBot to better interpret and respond to user queries in a more nuanced and contextually relevant manner. Additionally, integrating multimedia elements such as images or videos could enrich the user experience and provide additional context for medical information and advice [25]. Another potential area for improvement is in the integration of DocBot with external data sources and systems. While DocBot is designed to provide medical information and advice based on pre-existing knowledge within its training data, there may be opportunities to augment its capabilities by integrating with external databases, medical records systems, or other sources of relevant information. This could enable DocBot to provide more personalized and tailored responses based on individual user profiles, medical histories, and preferences. Moreover, the performance of DocBot's neural network model could be further optimized through techniques such as hyperparameter tuning, model architecture optimization, and ensemble learning approaches. By fine-tuning the model parameters and exploring alternative architectures, it may be possible to improve DocBot's accuracy, efficiency, and robustness across a broader range of tasks and domains.

In terms of future work, one potential direction is to explore the integration of advanced natural language processing (NLP) techniques, such as transformer models like BERT or GPT, into DocBot's architecture. These state-of-the-art models have demonstrated impressive performance in various NLP tasks and could potentially enhance DocBot's ability to understand and generate natural language responses. Additionally, expanding DocBot's capabilities beyond text-based interactions to include voice recognition and synthesis could further enhance its accessibility and usability, particularly for users with disabilities or those who prefer alternative modes of communication.

The GUI of DocBot was developed to give a user-friendly platform for accessing medical information, incorporating clear communication prompts and orderly presentation of responses [25].Through the training phase of the neural network, indicated by loss values across epochs, we noticed a steady drop in loss, indicating significant learning and adaption of the model's parameters. The GUI of DocBot was demonstrated to efficiently manage user requests, giving relevant and accurate information in a straightforward and structured manner. From welcoming messages to addressing sophisticated medical queries, the GUI prioritized simplicity, clarity, and reactivity, contributing to an enhanced user experience.

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