Thesis Proposal on:

The Power of Intent: Enhancing Chatbot Interactions

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1. **Introduction:**

Understanding the underlying intents of users' questions or remarks has emerged as a crucial facilitator for developing user-centric chatbots and virtual assistants in an era characterised by the widespread integration of artificial intelligence and human-machine interactions. The goal of this thesis proposal is to explore deeply into this fascinating area of human-computer interaction in order to provide the groundwork for the creation of chatbots and virtual assistants that can understand user intent in greater detail. According to a recent Tidio survey [1], 88% of consumers would have engaged in at least one conversation with a chatbot by 2022. These intelligent systems can provide more contextually appropriate responses by determining the user's intent behind their question or statement, considerably increasing their usefulness and efficiency in a variety of applications.

1. 1 **Background & Statement of the Problem:**

Human communication is complex and frequently filled with context, various degrees of ambiguity, and implicit indications. Traditional chatbots and virtual assistants have struggled to understand the underlying intent behind user input, relying mostly on rule-based or keyword-driven algorithms[2]. Responses as a result of this constraint may be contextually wrong or aggravate users. Therefore, the issue is to develop intelligent systems that can understand the user's genuine purpose, whether it be informational, transactional, emotional, or anything more nuanced, in addition to just interpreting words. The need for sophisticated natural language understanding models that can accurately identify and categorize user intent is the main issue that this thesis tries to address. This includes taking into account context, tone, attitude, and user-specific quirks in addition to the semantic meaning of words.

1.2 **Motivation:**

This research's inspiration comes from the goal of "humanizing" technology. Virtual assistants and chatbots have developed into essential tools in a variety of industries, including healthcare, education, and entertainment. We lower the cognitive load on users and promote more interesting and effective interactions by improving their capacity to recognize user intent. Moreover, the demand for empathy and contextual understanding grows as virtual assistants become more and more integrated into our daily lives.

1.3 **Challenges:**

The obstacles in our way are significant. Natural language is naturally complex, full of idiomatic terms, cultural quirks, and the opportunity for misunderstanding[3]. Context can also be dynamic and diverse. The creation and application of sophisticated machine learning techniques and algorithms that can extract both the explicit meaning and the implicit intent from user input is necessary to adapt to these difficulties.

1.4 **Objectives:**

The two main goals of this thesis are to survey and synthesize current research in natural language processing and intent recognition as well as state-of-the-art methods, and to suggest and develop novel techniques or algorithms that increase the precision and effectiveness of intent identification in chatbots and virtual assistants. The ultimate aim is to enable these technologies to have more user-centered, contextually aware, and emotionally intelligent dialogues.

Understanding User Intent: The main goal of this thesis is to examine in detail how to comprehend user intent. It's critical to understand what users are attempting to accomplish with their questions in the modern digital world, where chatbots and virtual assistants have ingrained themselves into every aspect of our lives. To increase the efficiency of AI-driven systems, this knowledge is essential.

Increasing the Efficiency of Virtual Assistants and Chatbots: This thesis aims to improve the effectiveness and efficiency of chatbots and virtual assistants by dissecting the layers of user intent. The ultimate objective is to make it possible for these AI systems to correctly understand and reply to customer inquiries, therefore offering helpful assistance and lessening user annoyance.

Enhancing User Experience: Improving user experience is another important goal. Chatbots and virtual assistants can give more pertinent and useful answers when they can accurately determine user intent. As a result, users have a more positive and effective user experience, which promotes user loyalty and trust.

Reducing User Effort: AI systems can lessen the effort users must exert during interactions by properly recognizing user intent. Users can communicate more organically by making requests or asking inquiries without having to utilize certain words or phrases. This increases the usability and accessibility of technology.

Natural Language Processing (NLP) Technique Advancement: This thesis also intends to develop NLP methodologies. Complex NLP algorithms and models are frequently needed in order to effectively recognize user intent. Enhancing these techniques can have beneficial effects on other NLP applications other than chatbots.

Personalization and customization: Chatbots and virtual assistants can tailor their replies by taking into account the user's purpose. In order to make the user experience more personalized and interesting, the thesis investigates how AI systems might modify their interactions depending on the distinct goals and preferences of individual users.

Scalability and Robustness: Addressing the scalability and robustness of intent recognition is another goal. These AI systems must be able to handle a variety of inquiries and scenarios with reliability because they are being used across several disciplines and sectors. The goal of the research is to create strategies that are flexible and effective in many settings.

Applications in the Real World: This thesis' study ultimately aims to have applications in the Real World. It strives to provide workable approaches and techniques that may be used to chatbots and virtual assistants in a variety of fields, including customer assistance, healthcare, and other areas.

To achieve the above objectives we will identify the intent in 4 categories:

1. Informational Queries.
2. Transactional Queries.
3. Navigational Queries.
4. Troubleshooting and Support Queries.

2. **Literature Review:**

Natural language processing (NLP) methods are one of the most widely used methods for determining user intent (Chen et al., 2023; He et al., 2023) [7]. Computer science's NLP discipline examines how computers and human language interact. In order to determine the purpose behind a user's request or comment, NLP methods can be utilized to extract meaning from text.

For instance, Ashish et al.'s[4] suggestion to characterize the user intent of online queries using k-means clustering is an example.130,000 web search engine queries were gathered for the study, and they were classified as informative, navigational, or transactional using a k-means clustering method based on a number of query features. According to the research, more than 75% of online searches (grouped into eight categories) are informative in nature, while transactional and navigational searches account for around 12% of all searches. Additionally, the findings indicate that there are eight clusters of online inquiries, with six clusters being mostly informative and one cluster each being predominantly transactional and navigational.

Researchers have created a variety of alternative methods for determining user intent in addition to NLP techniques. To determine user intent, for instance, some academics have developed rule-based systems (Li & Yang, 2023). Rule-based systems are collections of rules that may be used to compare user statements and queries to predetermined intentions.

The interaction between intent-classification and slot-tagging tasks in natural language understanding (NLU) for chatbots is explored by A. Nigam et al. in their study from [5]. It proposes a multi-staged approach that takes use of the connection between these tasks in order to handle real-world datasets, especially those with grammatical and non-native language faults. In order to enhance intent and slot-entity predictions later on, the study also proposes fuzzy entity matching. This promotes higher context awareness and flexibility in NLU applications, especially for non-native speakers. The following strategies and algorithms are mentioned in the paper. Recurrent neural networks (RNNs): These are used to anticipate subcategory and classify intent. The NER-1, NER-2, and NER-3 named entity taggers are used to identify entities in user queries. At successive phases, the matching's rigor varies. The named entity taggers are trained using Stanford CoreNLP using a variety of languages. Rule-Based Strategy: For subcategory categorization, a rule-based method using matching keywords and keyphrases is utilized. They used three types of queries as:

1. **Real-World User Queries:** The experiment's dataset was collected through crowdsourcing, according to the study. This collection is made up of actual user inquiries.
2. **Intents and Slot-Entities:** The research team manually assigned these user inquiries to the appropriate intents and slot-entities. The purpose of this procedure of tagging was probably to provide a tagged dataset for training and assessment.
3. **Non-native Queries:** According to the article, named entity taggers were trained using publicly accessible non-native datasets. These databases probably include questions from non-native speakers, which could include grammatical errors and unusual language usage.

They found accuracy for intent classification for Slot-Gated with Bi-LSTM with attention model is 63.97%.The accuracy found for intent classification using the BiLSTM with attention model for joint intent and slot tagging is 58.68%.The found accuracy for intent categorization in the multi-staged model (without varying NER at various stages) is 54.67%.The found accuracy for intent categorization using the multi-staged approach (without substituting entities with their tags) is 66.23%.Intent classification accuracy for the Final Multi-staged Model model was determined to be 75.07%.

In another research of L. P. Manik et al.'s [16] they achieved a goal is to analyse the function and difficulties of knowledge-based chatbots (KBCs), which leverage embedded knowledge and natural language processing (NLP) to help users locate information more quickly. Additionally, it presents a methodology to solve the difficulties associated with categorizing user inquiries as either in-scope (IS) or out-of-scope (OOS), and it makes suggestions for ways to boost KBC speed. They used the approaches and algorithms listed as: 1) Template-based Natural Language Generation (NLG): This method is presented to produce in-scope (IS) queries using an ontology provided as training data. 2) The Bayesian version of Bidirectional Encode Representations from Transformers (BERT) is a suggested approach for the classification of in-scope (IS) and out-of-scope (OOS) inquiries with little training data. It is a BERT model version customized for the particular classification assignment. They only employed two sorts of questions.

1. **In-Scope (IS) Queries:** These are inquiries that are either pertinent to the principal subject of interest or fall within the capabilities of the system. The categorization and effectiveness of models in responding to IS questions are covered in the text.

2. **Out-of-Scope (OOS) Queries:** These are inquiries that are either unconnected to the main issue or go beyond the capability of the system. The paper also addresses OOS query detection and categorization tests.

They attained the following accuracy percentages for various algorithms: for All models categorized IS questions with an F1 score greater than 80%. When categorizing IS questions, two iterations of the IndoBERT models ([28] and [30]) received a 100% F1 score. Model [29] used a learning rate of 5e-5 and a batch size of 16 to get the maximum F1 score of 98%. When categorizing IS intents on the test dataset, Google DialogFlow received a 100% F1 score after being trained with the produced IS training and validation dataset.

Another study conducted by A. Kathuria et al. [4] looked at the introduction and discussion of the role that search engines play in people's everyday life. It highlights the development of web searching, its distinctive qualities, and the variety of methods in which users make use of search engines. In order to better web search engine performance, the article poses concerns regarding how to comprehend user intent in web searches and provides a methodology using k-means clustering to categorize user intent. K-means clustering was used to categorize user intent in online searches. The main method described for classifying user searches based on intent and enhancing web search engine performance is K-means clustering. They used the following three different kinds of queries to train their model:

1. **Informational queries:** These inquiries look for information on certain issues or topics. On the list of examples are "flowering climbing vines" and "hazards on football fields."

2. **Navigational queries:** You may locate certain websites or groups of websites using navigational searches. The examples presented are "University of North Carolina" and "image search engines."

3. **Transactional Queries:** A specific transaction, like downloading software or making a purchase, is completed using a transactional query. The phrases "download hp simple backup" and "purchase camping gear" are given as examples.

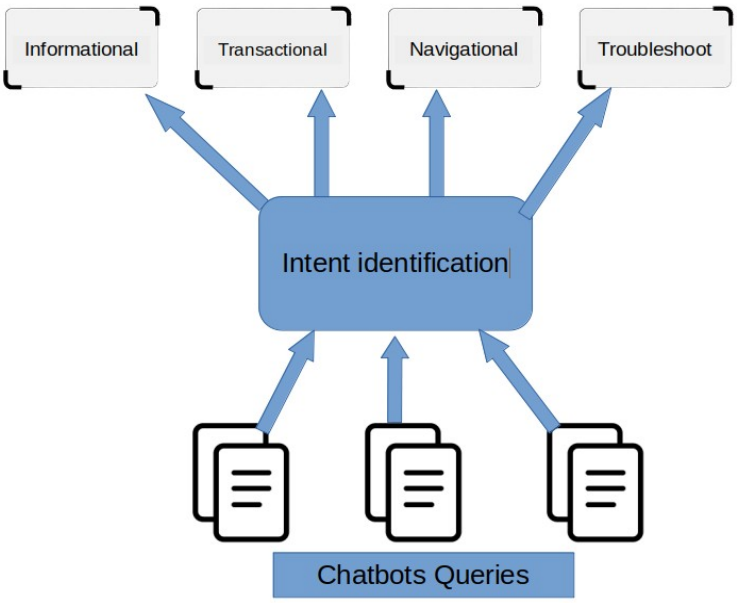
The accuracy for the K-means clustering method, which was used to categorize user intent in online searches, was as follows: The accuracy rate for the first run with 400 queries was about 88 percent, while the test data error rate was about 12 percent. The accuracy rate was almost 88 percent for the second run with 65,000 queries, while the test data error rate was roughly 12 percent. The accuracy rate was about 87 percent for the third run with 130,000 queries, while the test data error rate was about 13 percent.

A precise query intent classification approach utilizing convolutional neural networks (CNN) was introduced in Homa et al.'s study[6] using convolutional neural networks. It seeks to capture semantic similarities and enhance search engine performance by describing requests as vectors. By accurately identifying user intent, this method improves search results and makes it possible for more contextually aware answers. It makes a significant addition to query interpretation in contemporary search engines based on experimental results that show greater precision and recall compared to previous approaches. Their used algorithms are: CNNs, which stand for convolutional neural networks, question vectors are automatically extracted and used as features for query categorization and intent detection. To learn query vector representations, these CNNs are trained on top of word vector representations. The research utilizes a typical Random Forest classifier with 100 estimators for classification tests in order to test the CNN-based query intent detection technique. The study uses the k-Means clustering technique (k = 125) to group queries based on the embeddings that are taken from low-level intent classes. The query vectors acquired from the CNN are used for this clustering. They gathered the search terms from the records of a commercial search engine for their studies. For the aim of testing the query intent detection technique, these queries were manually annotated in order to produce a dataset comprising queries and the associated intents. The dataset contains more than 3800 intents at the lowest level and 350 at the highest level, even if the text doesn't give explicit instances of the sorts of queries done. They got the accuracies for:

For Low-Level Intent Detection: CNN: 81.6%

For High-Level Intent Detection: CNN: 90.3%

3. **Research Techniques:**



3.1 **Data gathering:**

assemble a broad and representative collection of user inquiries or declarations along with the underlying intentions. We will use one dataset from the biggest data science forum in the world is Kaggle (CLINC150)[9] and another one dataset that we will collect from various chatbots and virtual assistants through API.

From the following table this is the clear view of the nature of the queries of Informational Queries, Transactional Queries, Navigational Queries, Troubleshooting and Support Queries. The preview of our data set will be looked like as:

Informational Queries	**Transactional Queries**	**Navigational Queries**	**Troubleshooting and Support Queries**
"What is the capital of France?"	"Order a large pepperoni pizza for delivery."	"Navigate to the homepage of your website."	"I can't access my email account. What could be the problem?"
"Tell me about the benefits of meditation."	"Book two tickets for the 7:00 PM movie at the nearest cinema."	"Open the settings menu."	"My printer isn't responding. What should I do?"
"Who wrote the 'Moby-Dick' novel?"	"Purchase a red handbag with a matching wallet."	"Take me to the nearest gas station."	"Why is my computer running so slowly?"

"Explain the concept of climate change."	"Transfer $50 to Shanta's bank account."	"Directions to 123 Main Street, New York."	"My Wi-Fi isn't working. Can you help me troubleshoot?"
"Give me an overview of the solar system."	"Add two copies of 'The Great Gatsby' to my shopping cart."	"How do I get to the customer support page?"	"I forgot my password. How can I reset it?"

3.2 **Data preparation:**

An essential phase in the research process is data preparation. To maintain consistency and quality, the obtained data must be cleaned and refined. The elimination of stop words, tokenization, and text normalization are crucial duties in this phase. To preserve uniformity, text normalization standardizes the text by, for example, changing capital to lowercase. Tokenization separates text into smaller pieces for examination, such as words or phrases. Eliminating common words like "and" or "the" allows readers to concentrate on the stuff that matters. By decreasing noise and inconsistencies in the data, these methods improve the dataset's quality and prepare it for analysis, ensuring that study findings are more accurate and dependable. [10].

3.4 **Extracting Features:**

We try to collect the most pertinent details that aid the model in deciphering the text's underlying meaning while extracting features for intent classification from preprocessed text data. Word embeddings and TF-IDF vectors are two popular methods for feature extraction. Word embeddings that capture semantic linkages, such Word2Vec or GloVe, convert words into dense vector representations. These embeddings provide the model the ability to comprehend word context and similarity, which is essential for deciphering user intent. It can tell, for instance, that the words "buy" and "purchase" indicate comparable things [12].

The significance of words inside a document with relation to a corpus, however, is represented by TF-IDF vectors. Higher TF-IDF ratings are assigned to words that are common in one text but uncommon across the whole corpus, emphasizing their importance. This method aids the model's attention to terms that reflect user intent. Intent classification models may more accurately identify user intentions within text data by using these feature representations, which leads to increased accuracy in tasks like chatbot answers and natural language comprehension.

3.4 **Choosing algorithm:**

We'll utilize three machine learning algorithms to see which one produces the best results as we categorize user questions into four categories for our thesis project: informational queries, transactional queries, navigational queries, and troubleshooting and support inquiries.

3.4.1 **Support Vector Machines (SVM)**

Support Vector Machines (SVM), one of the three algorithms, is a top contender for this job [11]. Why SVMs may be a wise choice is as follows:

Multi-Class Classification: SVMs naturally handle multi-class classification issues like the one we have. To classify queries into the four groups, we may use SVM with one-vs-rest (OvR) or one-vs-one (OvO) techniques.

Effective Class Separation: SVMs search for the hyperplane that optimizes the margin between classes, which can be particularly helpful when the classes are clearly defined or when the decision boundaries are intricate.

Flexibility in Feature Representations: SVMs may successfully use a variety of feature representations, such as Word2Vec or TF-IDF vectors, which are frequently employed in text classification problems.

Robustness: SVMs are capable of handling unbalanced datasets, a problem that frequently arises in applications involving natural language processing where certain query patterns may be less common.

Regularization: SVMs provide regularization options to assist avoid over-fitting.

Interpretability: SVMs offer results that are easy to understand, which is useful for figuring out how and why a certain query got put into a given category.

3.4.2 **Random Forest Classifier**

In our thesis research, categorizing user inquiries into the four categories using the Random Forest Classifier machine learning algorithm can potentially be a practical choice. Here's why it could be a wise decision:

Multi-Class Classification: Random Forest is suited to our issue since it naturally handles multi-class classification problems.

Ensemble Learning: Random Forest is an ensemble learning technique that blends many decision trees to enhance classification performance in general. This can lessen over-fitting and strengthen the model.

Feature significance: Random Forest calculates a feature significance score that may be used to determine which words or features have the most influence on categorization outcomes. This realization may be helpful for interpretation and more research.

Robustness: In NLP jobs where text input might be untidy, Random Forest's overall robustness to outliers and noisy data can be useful.

Usefulness: Compared to certain other algorithms, like SVM, Random Forest is very simple to develop and requires fewer hyper-parameters to be tuned.

Parallelization: Individual decision trees can be trained in a Random Forest in concurrently, which can speed up the training process on multi-core processors or in remote computing settings.

3.4.3 **Gradient Boosting Algorithm**

In our thesis research, categorizing user inquiries into the four categories may also be accomplished by using gradient boosting techniques like XGBoost or LightGBM. Here's why it could be a wise decision:

excellent Accuracy: Gradient Boosting algorithms frequently exhibit excellent accuracy and predictive performance, which makes them suitable for challenging classification problems.

Ensemble Learning: Gradient Boosting is an ensemble learning approach that, like Random Forest, combines a number of weak learners (decision trees) to produce a powerful prediction model. This enhances the generalization and performance of the model.

Feature Importance: Gradient Boosting algorithms can generate feature relevance scores, which let us know which words or attributes have the most impact on categorizing user queries. This can offer insightful information on the classification process.

Robustness: Gradient Boosting techniques are good at handling noisy data and outliers, which is crucial for natural language processing jobs where text data might be unorganized.

Flexibility: These algorithms are able to handle a variety of feature types and can identify intricate links in the data.

Hyper-parameter Tuning: To improve performance for our particular dataset and job, we may fine-tune hyper-parameters like the learning rate, the number of boosting rounds, the tree depth, and the regularization terms.

Balanced Classes: Gradient Boosting techniques are capable of handling unbalanced datasets, preventing dominant query types from overshadowing unusual query types.

3.5 **Convolutional Neural Networks (CNNs)**

The choice of a Convolutional Neural Network (CNN) algorithm for our thesis project, where we aim to categorize user queries into four categories (Informational, Transactional, Navigational, Troubleshooting, and Support Queries), can depend on a number of factors, including the complexity of our data and the resources available. Two CNN algorithms that will be employed in our research are listed below:

3.5.1 **Siamese Networks**

Siamese networks are mostly made for similarity-based tasks, such comparing two inputs' similarity. Siamese networks may be helpful if our intent classification objective entails finding questions that are similar to predetermined intent queries. Siamese networks, on the other hand, could need a more intricate setup and are frequently employed in one-shot or few-shot learning scenarios when we have a limited number of labeled samples.

3.5.2 **Long Short-Term Memory (LSTM) Networks**

Because LSTM perform well with sequential data, LSTM networks are a good choice for text categorization applications. LSTM networks may be a viable option if our user queries contain substantial sequential dependencies or context that affects intent categorization. They are able to identify distant relationships in the text, which may be crucial for deciphering human intent.

3.6 **Model Training:**

A crucial step in machine learning is model training, where we instruct our algorithms to generate predictions based on the data we have. The training set, validation set, and test set will be the first three subsets we divide up in our method. We can more accurately assess the model's performance thanks to this divide. For our intent classification challenge, we want to use Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). SVMs work well for data that can be separated into lines, but CNNs are excellent at identifying intricate patterns in sequential data, like as text. Our chosen characteristics, such Word2Vec or TF-IDF representations, are fed into these models during the training process. We'll run experiments, including hyper-parameter tuning, to improve our models. This entails changing CNN parameters like the number of layers, the size of the filters, and the learning rates. We can identify the ideal mix for our unique work with the aid of hyper-parameter optimization. We seek to attain the best accuracy and robustness in our intent classification models by iterating through these training and tuning procedures, making sure they can accurately grasp and categorize user intentions inside text data.

4. **Expected result:**

4.1 **Evaluation Metrics:**

In our thesis research, evaluation measures are essential for appropriately evaluating the effectiveness of our intent classification models. These metrics give us quantifiable information on how successfully our models classify user inquiries into the four types that they fall under: informational, transactional, navigational, and troubleshooting and support queries.

Accuracy: This score assesses the general accuracy of our model's forecasts. We must make sure that our model is not biased toward any one group in particular.

Precision: Precision reveals the percentage of incidents within each category that were accurately predicted. It allows us to evaluate how well our model prevents false positives. Precision measures the proportion of true positive predictions among all positive predictions made by the model. It is calculated using the formula:

$$P = TP / (TP+FP)$$

Where:

- TP (True Positives) is the number of correctly predicted positive instances.
- FP (False Positives) is the number of incorrectly predicted positive instances.

Recall: The proportion of actual instances that the model accurately predicted, also known as recall or sensitivity, is measured. It's essential for spotting erroneous negatives. Recall measures the proportion of true positive predictions among all actual positive instances. It is calculated using the formula:

$$R = TP / (TP+FN)$$

Where:

- TP (True Positives) is the same as in the precision calculation.
- FN (False Negatives) is the number of actual positive instances that were incorrectly predicted as negative.

F1-Score: The harmonic mean of recall and accuracy is known as the F1-Score. It is a balanced measure that takes into account both false positives and false negatives, making it appropriate for datasets that are unbalanced. The F1 score is the harmonic mean of precision and recall, combining both metrics into a single value. It is calculated using the formula:

$$F1 = (2 \cdot P \cdot R) / (P+R)$$

This formula balances precision and recall, giving equal importance to false positives and false negatives. The F1 score ranges from 0 (worst) to 1 (best), where higher values indicate better model performance in terms of both precision and recall.

4.2 **Evaluation and comparison:**

We aim to evaluate and compare the performance of four different intent classification models in this comparative analysis: Random Forest Classifier, Gradient Boosting Algorithm, Siamese Networks, and Long Short-Term Memory (LSTM) Networks. Within the framework of user intent identification, we seek to thoroughly analyse their accuracy, computational efficiency, and generalization capacities.

Accuracy: The accuracy of each model's classification of user questions into the preset intent categories (Informational, Transactional, Navigational, Troubleshooting, and Support questions) will be closely examined. In order for chatbots and virtual assistants to function properly, high accuracy means a stronger capacity to accurately ascertain user intent.

Efficiency: Efficiency is essential, especially in real-time applications, in addition to accuracy. We will evaluate each model's viability by taking into account variables like training time, inference speed, and resource use.

Generalization: Ability to generalize is essential for ensuring that models work effectively with untested data. We will evaluate each model's capacity to generalize to new, unforeseen user inquiries, which is essential for the resilience and flexibility of chatbot systems.

We intend to offer insight on how each algorithm approaches the particular difficulties of user intent recognition by comparing differences in accuracy, efficiency, and generalization across various models. This study will offer insightful information about the advantages and disadvantages of each strategy, assisting in the choice of the best model for your particular intent classification problem.

5. **Documentation and Reporting:**

The study findings, procedures, and results will be completely recorded for open communication during the documentation and reporting phase. The dataset, data preparation procedures, feature extraction methods, and the training of the Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs) models are all covered in length in this documentation. Results of the evaluation, which will be provided, will include accuracy, precision, recall, F1-score, and any variations between the two methods that were noticed. We'll go into great detail on ethical issues, bias mitigation techniques, and potential implications for the creation of chatbots and virtual assistants. This documentation supports a clear understanding of the study's contributions and assures the research's repeatability.

6. **Conclusion:**

As a crucial part of chatbots and virtual assistants, intent categorization in the context of user questions has been thoroughly explored in this thesis. The performance of four different models—Random Forest Classifier, Gradient Boosting Algorithm, Siamese Networks, and Long Short-Term Memory (LSTM) Networks—was rigorously assessed and contrasted. Our data will show that each model demonstrates distinct advantages and disadvantages. Intent identification algorithms Random Forest and Gradient Boosting performed exceptionally well in terms of accuracy. Siamese Networks demonstrated success in tasks based on similarity, whereas LSTM Networks demonstrated mastery over sequential data. Random Forest and Gradient Boosting are suited for real-time applications because to their computational benefits, according to efficiency evaluations. Assessment of generalization revealed that LSTM Networks had higher adaptation to unknown input. The final decision on the model depends on the particular needs of the application. Informed decisions on the implementation of chatbot and virtual assistant systems may be made thanks to the useful insights provided by our thesis into the complex terrain of intent classification.

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