Unveiling the Untapped Potential of Zero-Shot Text Classification

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by

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May 2022

I dedicate my thesis to my friends and family.

DECLARATION

I hereby declare that this project work entitled **Unveiling the Untapped Potential of Zero-Shot Text Classification** is original and has been carried out by me in the Department of Information and Communication Technology of Manipal Institute of Technology, Manipal, under the guidance of **Dr. Girija Attigeri**, **Associate Professor**, Department of Information and Communication Technology, M. I. T., Manipal. No part of this work has been submitted for the award of a degree or diploma either to this University or to any other Universities.

Place: Manipal

Date : 20-05-24

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CERTIFICATE

This is to certify that this project entitled **Unveiling the Untapped Potential of Zero-Shot Text Classification** is a bonafide project work done by **Mr. Akhil Rahman (Reg.No.:200953061) and Mr. Sushant Raj (Reg.No.:200953062)** at Manipal Institute of Technology, Manipal, independently under my guidance and supervision for the award of the Degree of Bachelor of Technology in Computer and Communication Engineering.

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ABSTRACT

Text classification in the modern world serves as a cornerstone in effectively organizing and understanding vast amounts of textual data, aiding organizations and businesses to attain better decision making and insights. As advancements in technology continue to rise, the demand for enhanced methods in every domain, including text classification, surges. Zero shot text classification emerges as an innovative paradigm shift that revolutionizes traditional classification approaches by enabling models to accurately classify text without the need for explicit training on every possible class.

In this paper, we have implemented the facebook/bart-large-mnli model from Hugging Face Transformers on the three datasets: Amazon Reviews, Twitter User Data, and Restaurant Reviews for sentiment classification. This entails accurately categorizing the textual data based on their underlying sentiment. Furthermore, we compare the performance of zero-shot learning on these datasets with conventionally deployed supervised learning techniques such as Naive Bayes, Support Vector Machine (SVM), and Recurrent Neural Networks (RNN), by employing metrics such as F1 score, precision, and recall.

Upon comparison with conventional supervised learning techniques, our study revealed that zero-shot text classification achieved impressive accuracies of 0.92, 0.93, and 0.98 on the respective datasets, emphasizing the effectiveness of this approach. This outcome is noteworthy as it demonstrates the capability of ZSL in accurately classifying text based on sentiment without the need for explicit training on every possible class.

[Computing Methodologies]: Machine Learning - Machine Learning Approaches- Kernel Methods - Support vector machines; Learning in probabilistic graphical models - Bayesian network models

[Information Systems]: Information Retrieval - Retrieval tasks and goals - Sentiment Analysis

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ABBREVIATIONS

BART	:	Bidirectional and Auto-Regressive Transformer
BERT	:	Bidirectional Encoder Representations from Transformer
GRU	:	Gated Recurrent Unit
MNLI	:	Multi-Genre Natural Language Inference
NLI	:	Natural Language Inference
NLP	:	Natural Language Processing
RNN	:	Recurring Neural Networks
SVM	:	Support Vector Machines
TD-IDF	:	Term Frequency Inverse Document Frequency
ZSL	:	Zero-Shot Learning

NOTATIONS

x	:	Input text
Y	:	Set of candidate labels
h_i	:	Hypothesis for the label y_i
$\mathbf{E}_x$	:	Encoded representation of the input text
$\mathbf{E}_{h_i}$	:	Encoded representation of the hypothesis h_i
W_Q, W_K, W_V	:	Weight matrices for query, key, and value transformations
$\mathbf{Q}_x$, $\mathbf{K}_x$, $\mathbf{V}_x$	:	Query, key, and value matrices for input text
$\mathbf{Q}_{h_i}$, $\mathbf{K}_{h_i}$, $\mathbf{V}_{h_i}$	:	Query, key, and value matrices for hypothesis
Attention($\mathbf{Q}_x$, $\mathbf{K}_{h_i}$, $\mathbf{V}_{h_i}$)	:	Attention mechanism comparing $\mathbf{Q}_x$ with $\mathbf{K}_{h_i}$ and $\mathbf{V}_{h_i}$
Score_i	:	Entailment score for hypothesis h_i
$p(y_i \mid x)$	:	Probability of the label y_i given the input text x

Chapter 1

Introduction

In the current digital era, billions of text data, comprising both structured and predominantly unstructured data are available in the form of news articles, social media content, emails and reviews. Classifying these textual information into predefined categories is an important aspect of NLP. The resulting outcome helps in a wide variety of applications such as sentiment analysis, intent detection and topic classification.

Conventional NLP text classification approaches such as Naive Bayes and SVM, not to mention deep learning models like RNN, have established their proficient ability in classifying text. However, their dependency on labeled data for each category and the necessity to retrain the model with additional examples whenever a new category is introduced, make them a liability.

The report explores how zero-shot text classification alleviates the challenges linked with the aforementioned NLP text classification methods by eradicating the need for explicit training on each category. This can be achieved with the help of pre-trained language models that are trained on an vast collection of textual data. By utilizing the semantic knowledge gained from these models and tasks like fine-tuning, ZSL can accurately predict labels for the new text data.

Our motivation for this work stems from the need to explore the potential of the BART (Bidirectional and Auto-Regressive Transformers) model in text classification, in comparison to the BERT (Bidirectional Encoder Representations from Transformers) model utilized in the referenced paper. BART demonstrates superiority over BERT, especially in scenarios where context and sequence order are critical. Compared to BERT's bidirectional approach, BART model comprises an auto-regressive architecture that aids in fine-tuning for specific tasks like text classification. This combination of bidirectional pre-training and auto-regressive decoding is one of the key features that distinguishes BART from models like BERT.

1.1 Objectives

- Implement Zero-Shot Learning (ZSL) and traditional text classification methods (Naive Bayes, SVM, RNN) on multiple datasets of varying sizes.
- Inspect the performance of each text classification technique using metrics like accuracy, F1-score, precision and recall, to identify the most effective method.
- Compare the effectiveness of ZSL and other traditional text classification methods across datasets, analyzing their generalizability and robustness.
- Visualize the results using bar graphs to offer a precise analogy of the performance of different classification methods.

1.2 Importance of the End Result

The findings of this study can facilitate companies in analyzing customer feedback from reviews and social media content, thereby enabling businesses to understand customer sentiment towards a particular product or service, and how they can be improved to satisfy the customer. Another distinctive application involves monitoring mental health through social media and other platforms. By analyzing the sentiment of posts and comments, we could identify individuals at risk of mental health issues like depression and provide the necessary support to overcome it. Zero-shot text classification can be used in the political arena as well to determine public opinion of politicians and policies. By categorizing sentiments related to various political issues, researchers and policymakers would be able to understand public opinion and implement the necessary strategies to appease the people.

1.3 Organization of Project Report

The remaining report is organized as follows: Chapter 2 comprises literature review. The methodology followed by the model architecture of ZSL are portrayed in Chapter 3. Chapter 4 highlights the project carried out and the corresponding results comprising tables, graphs and screenshots are showcased in Chapter 5. Conclusion and future scope of ZSL are discussed in Chapter 6.

Chapter 2

Literature Survey

Evaluation of Healthprompt for Zero-shot Clinical Text Classification authored by S Sivarajkumar et al. (2023) uses Pre-trained Language Models (PLMs) and prompt-based Zero-Shot Learning (ZSL) for classifying medical text without needing extra training data. Healthprompt's capabilities and constraints are investigated in this study through an error analysis and elimination probe on the Electronic Health Records (EHR) notes. Results show that Healthprompt performs best with a token limit of 250 and faces challenges with shorter clinical notes and complex chronological EHRs. The discoveries highlight the importance of the chunk encoding mechanism for capturing context in long clinical documents and suggest future research directions for improving Healthprompt's performance in clinical NLP tasks [1].

The paper ”Detection of Novel COVID-19 Variants with Zero-Shot Learning” by Sayantani Basu, Roy H. Campbell, and Karrie Karahalios et al. (2023) presents a pioneering method utilizing Siamese Neural Networks (SNNs) for the swift detection of new COVID-19 variants without the necessity to retrain on the complete dataset. It highlights the limitations of deep learning models in diagnosing new variants, and suggests exploiting the ZSL approach that utilizes learned embeddings from the first few COVID-19 variants. This is attained by training the SNN model on the prevailing variants. The corresponding accuarcies of 96.95 percent and 96.42 percent in training and validation respectively, signifies the efficacy of this approach in detecting the emerging variants. This study promises a great potential in enhancing public health surveillance amidst the ongoing COVID-19 pandemic by delivering critical information into the evolution and transmission of the virus [2].

”Enhancing Class Understanding via Prompt-Tuning for Zero-Shot Text Classification” authored by Yuhao Dan et al. (2022) describes a ZSTC) approach that enhances the semantic understanding of each class and identifies the relationships between the texts and the corresponding classes. By utilizing a prompt matching model, it determines the matches between the respective text and class and employs prompt inserting technique to produce the corresponding words for class descriptions. Three benchmark datasets have been considered and an exceptional performance on unseen classes was achieved, thus showcasing the effectiveness of the method. By utilizing the pre-trained language models, we observe the improvement of ZSTC, that requires no dependence on human labour or external knowledge sources [3].

The paper, titled ”Zero-Shot Approach for News and Scholarly Article Classification” compares the efficiency of the Multi-Nomial Naive Bayes approach and the Zero-Shot Learning method in the field of text classification particularly in the BBC News and ArXiv datasets. Achieving a top-2 accuracy of approximately 93 percent and 87.6 percent on the two datasets, the study indicates that Zero-Shot Learning demonstrates exemplary performance when compared to the conventional Naive Bayes model. By leveraging the semantic relationships acquired between the seen and unseen classes, ZSL classifies the data without requiring previous training, thus enabling fruitful text classification even with additional categories [4].

The paper ”A Comparison of Zero-Shot Text Classification and Rule-Based Matching for Detecting Cyberbullying Behaviors on Social Media” by Chong, Chua, and Gan et al. (2022) from Sunway University, focuses on detecting cyberbullying instances from the content shared on social media platforms. Both zero-shot classification as well as rule-based matching are evaluated against human annotation. The findings of this study points out that zero-shot classification effectively identifies aggressive behavior from the text data. Rule-based matching, on the other hand, exhibits greater accuracy in texts that contain and racism content. The paper finally concludes by mentioning that further improvements are necessary for the zero-shot model to predict various other kinds of cyberbullying behaviors across social media platforms, efficiently [5].

”Generalized Zero-shot Learning for Entailment-based Text Classification with External Knowledge” by Wang et al. (2022) addresses the challenge of classifying texts with limited or no training data at all, a method popularly known as zero-shot learning. The paper puts forward a novel approach that utilizes entailment relationships acquired between the text and the external information to improve classification accuracy. A distinguishing factor is that this method incorporates the external information efficiently, thereby piloting to better performance in scenarios where labeled data is scarce [6].

The paper, titled ”Zero-Shot Learning for Text Classification: Extending Classifiable Beyond Conventional Techniques” (2023) by Palaniappan et al., explores the shortcomings of existing NLP text classification techniques. These methods heavily rely on explicit training for each label to classify text, which makes it a burden since data availability for each class is limited. The AG news dataset is chosen for this paper and is subject to text classification by neural networks like RNN and CNN. Zero-shot text classification is also applied on this dataset and the performance metrics of all these models are evaluated. ZSL emerged as a superior text classification approach attaining an accuracy of 99 percent [7].

The paper “Knowledge-Embedded Prompt Learning for Zero-shot Social Media Text Classification” by Li et al. (2023) addresses the difficult ask of obtaining insights from social media content. Although deep learning has displayed promise in assessing such data, its efficiency has been curbed due to its frequent necessity of huge amounts of labeled data. These limitations are addressed by introducing zero-shot text classification. Considered a novel approach, this method leverages knowledge embedded prompt learning. By experimenting on several datasets, this method proves its dominance over existing NLP methods, thus providing a more efficient and accurate social media data analysis [8].

The paper ”Cost Effective Annotation Framework Using Zero-Shot Text Classification” (2023) by Kasthuriarachchy et al. addresses the high cost limitations related to data annotation in machine learning tasks, especially when large and uneven datasets are dealt with. Zero-shot text classification which aims to classify text without requiring labelled data for every category, is proposed. Pre-annotating the textual data with a zero-shot classifier, drastically reduces the dependence on human annotators. Accurate classifications are achieved using this model resulting in major cost reductions. This research aims to make data annotation more proficient and cost-effective for large-scale datasets [9].

The paper ”Generalized Zero-Shot Text Classification via Inter-Class Relationship” authored by Zhang et al. (2023) investigates an innovative method for generalized zero-shot text classification. The model classifies text into unseen categories without any labeled data for those categories. The limitations of existing NLP methods are discussed, thereby arriving at a proposition that aims to incorporate inter-class relationships. This approach helps capture the semantic connections between different categories by exploiting external information beyond the text itself. Understanding these relationships, helps the model comprehend and distinguish between unseen classes even in the absence of labeled examples, thus leading to enhanced classification accuracy [10].

Chapter 3

Methodology

The methodology section comprises of a clear description of the three datasets used in this project, the notion of the pre-trained model and its functionality, and explains the ZSL model architecture as well as that of traditional supervised learning models.

3.1 Description of the Three Datasets

Our first dataset consists of Amazon product reviews. These reviews vary from a few lines of text to a complete paragraph. Each review text belongs to either “label 1” that conveys negative sentiment or ”label 2” that conveys positive sentiment. These are the ground truth labels that enable us to compare the accuracy and other evaluation metrics with other NLP text classification techniques.

The second dataset includes various kinds of user tweets and the corresponding sentiment: 0 for positive tweet and 1 for negative tweet. This facilitates in analyzing the emotional sentiment behind the respective user tweet. The text within each user tweet are not necessarily whole and coherent sentences, rather they are fragmented.

The last dataset contains restaurant reviews given by customers and the ground truth label for each customer review. Positive reviews are denoted by 1 and negative reviews are denoted by 0. Based on the reviews, the restaurant can improve its food and services and increase customer satisfaction.

3.2 Pretrained Language Model

A pretrained language model is defined as one that has been trained on a huge corpus of textual data to comprehend and understand human language. Due to its exposure to such a vast amount of text, it has learnt to grasp the patterns, relationships and principles that govern human language. Once the model is pretrained, it can be fine-tuned on specific tasks or datasets to adapt its understanding to various domains. Text classification, sentiment analysis, language translation and summarization are few examples that a pretrained language model can be fine-tuned on.

In this study, we have employed the facebook/bart-large-mnli model from the Hugging Face Transformers library as our pretrained language model. Facebook AI has developed a model architecture called BART (Bidirectional and Auto Regressive Transformers). Utilizing a denoising autoencoder objective for pretraining, this transformer-based sequence-to-sequence model learns to restructure the initial original sentence from its distorted form. The pretraining process aids BART in comprehending the syntax and semantics of text written in natural language.

The ”facebook/bart-large-mnli” model from the Hugging Face Transformers library is a specific variant of the BART model that has been fine-tuned on the MNLI dataset. This is a benchmark dataset for natural language understanding tasks, predominantly for textual entailment and natural language inference. This specific variant of the BART model is optimized for tasks that involve understanding the relationships between sentences, thereby well-suited for applications such as text classification, question answering, and summarization.

The Facebook BART Large MNLI model is a powerful pre-trained model for zero-shot classification. It leverages the pre-trained weights from the BART model and the MultiNLI dataset for transfer learning.

3.3 ZSL Model Architecture

The general workflow for the proposed project is depicted in Figure 3.1. The BART model as illustrated in Figure 3.2, comprises of 12 encoder layers and 12 decoder layers amounting to a total of 24 layers. Each layer in the encoder and decoder has sub-layers which comprises of Self-Attention Mechanism and Feedforward Neural Network. The decoder layer has an additional sub-layer known as the Cross-Attention Mechanism.

The Facebook BART Large model is a larger version of the base BART model. It encompasses more parameters and has higher capacity for learning complex patterns in the text data. Naturally, due to the model's large size, we can achieve better performance in NLP tasks encompassing text classification, machine translation, and summarization."

Ultimately, the Facebook BART Large model is fine-tuned on the MNLI dataset to aid the model in understanding the relationship between a pair of sentences and to assess where one sentence entails the other sentence or not. The knowledge gained during fine-tuning can be leveraged to implement zero shot text classification where the model can generalize to new, unseen classes by deducing relationships between the input text (premise) and the candidate labels (hypothesis). Samples of the MNLI dataset are shown in Figure 3.3. to get a better understanding of the entailment concept.

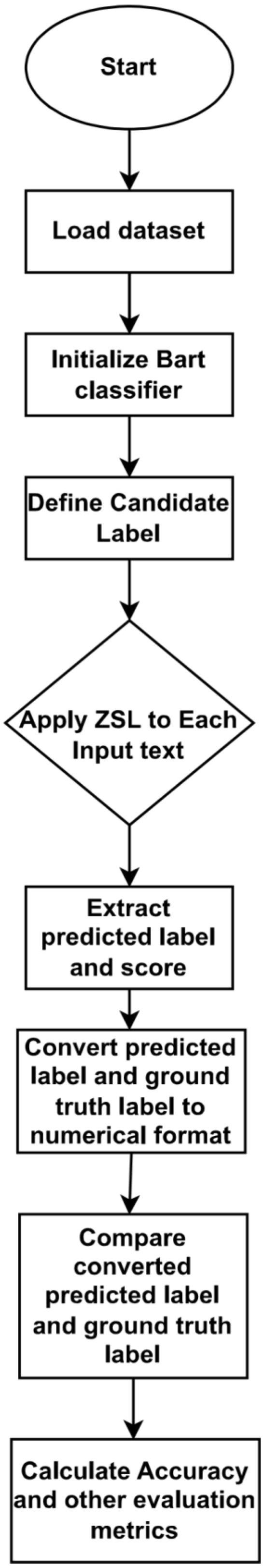

Figure 3.1: ZSL text classification pipeline using Facebook BART Large MNLI

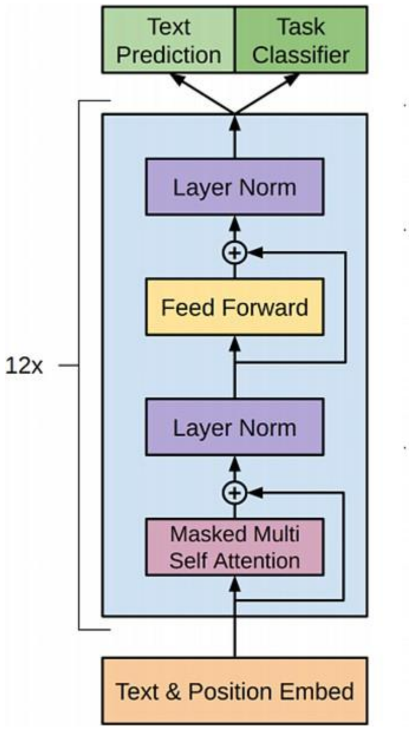

Figure 3.2: Transformers BART Model

Premise	**Label**	**Hypothesis**
Fiction		
The Old One always comforted Ca'daan, except today.	*neutral*	Ca'daan knew the Old One very well.
Letters		
Your gift is appreciated by each and every student who will benefit from your generosity.	*neutral*	Hundreds of students will benefit from your generosity.
Telephone Speech		
yes now you know if if everybody like in August when everybody's on vacation or something we can dress a little more casual or	*contradiction*	August is a black out month for vacations in the company.
9/11 Report		
At the other end of Pennsylvania Avenue, people began to line up for a White House tour.	*entailment*	People formed a line at the end of Pennsylvania Avenue.

Figure 3.3: Samples of then MNLI dataset

3.4 Mathematical Representation of facebook/bart-large-mnli model

In our methodology, we employ a systematic approach for zero-shot text classification, utilizing a BART tokenizer to preprocess both input text and candidate labels. Let us denote the input text as x, and the corresponding set of candidate labels as $Y = \{y_1, y_2, y_3, \ldots, y_n\}$. The input text is tokenized using the BART tokenizer, resulting in a sequence of token IDs, denoted as Tokenize(x). This sequence is usually represented as a vector:

$$\text{Tokenize}(x) = [x_1, x_2, x_3, \ldots, x_n]$$

The vector comprises numerical values where each number indicates a unique token ID mapping to specific words or sub-words within the model's vocabulary. These token IDs serve as the input for subsequent processing and classification within the BART model.

Likewise, for each candidate label y_i, we formulate a hypothesis h_i in the form "This text is about y_i". Each hypothesis h_i undergoes tokenization, generating a sequence of token IDs, represented as Tokenize(h_i). This vector sequence, denoted as $[h_{i1}, h_{i2}, h_{i3}, \ldots, h_{im}]$, consists of numerical values corresponding to token IDs associated with specific words or sub-words within the model's vocabulary.

Next, we leverage the BART Encoder to process the tokenized input text x, and its corresponding tokenized hypothesis h_i yielding their respective encoded representations denoted as E_x and E_{h_i}. The BART Encoder is skilled at capturing semantic nuances within textual data and plays a fundamental role in extracting meaningful features from the input sequences.

Mathematically, the process unfolds as follows:

$$E_x = \text{BART ENCODER}(\text{Tokenize}(x))$$

$$E_{h_i} = \text{BART ENCODER}(\text{Tokenize}(h_i))$$

For each hypothesis h_i, we employ an entailment scoring mechanism to quantify the similarity between the input text x and the hypothesis h_i, facilitated by a dot product attention mechanism. The entailment score is computed as:

$$\text{Score}_i = \text{Attention}(E_x, E_{h_i})$$

To derive the entailment score, we employ linear transformations on the encoded representations of the input text E_x and the hypothesis E_{h_i}, generating the query, key, and value matrices. These transformations are governed by weight matrices W_Q, W_K, and W_V, producing the query Q_x, key K_x and value V_x matrices for the input text (premise), and the corresponding Q_{h_i}, K_{h_i} and V_{h_i} matrices for the hypothesis.

$$Q_x = E_x \cdot W_Q$$

$$K_x = E_x \cdot W_K$$

$$V_x = E_x \cdot W_V$$

$$Q_{h_i} = E_{h_i} \cdot W_Q$$

$$K_{h_i} = E_{h_i} \cdot W_K$$

$$V_{h_i} = E_{h_i} \cdot W_V$$

To establish the semantic relationship between the input text and the hypothesis, we incorporate a cross-attention mechanism, which meticulously compares each component in the input text (premise) to every component in the hypothesis. This mechanism is essential in understanding the refined connections between the input text and the hypothesis.

The cross-attention mechanism is computed as follows:

$$\text{Attention}(Q_x, K_{h_i}, V_{h_i}) = \text{softmax}\ \frac{Q_x K_{h_i}^T}{\sqrt{d_k}}$$

Here, d_k denotes the scaling factor.

Subsequently, the entailment score is computed by taking the dot product of the attention score, the value matrix of the hypothesis V_{h_i}, and the transpose of the encoded representation of the input text E_x:

$$\text{Score}_i = \text{Attention}(Q_x, K_{h_i}, V_{h_i}) \cdot V_{h_i} \cdot E_x^T$$

These entailment scores are then transformed into probabilities using the softmax function. This conversion ensures that the output probabilities sum up to 1, thereby enabling a clear interpretation of the model's confidence score in each candidate label. For each candidate label y_i, the probability $p(y_i|x)$ is computed as:

$$p(y_i|x) = \text{softmax}(\text{Score}_i)$$

After computing the probabilities for each label, the label with the highest probability is selected as the predicted label for the input text. Mathematically, it is represented as:

$$y = \text{argmax}_i p(y_i|x)$$

The corresponding predicted label is subsequently compared with the ground truth labels of each input text to measure the accuracy and other evaluation metrics of the model. We can evaluate the ZSL model's efficacy and performance, not to mention how well it generalises to unseen data, through this comparison.

3.5 Naive Bayes Model Architecture

The Multinomial Naive Bayes classifier, used in this research, is a probabilistic machine learning model that calculates the probability of a category given the input text. It operates according to the Bayes theorem and relies on the assumption that the presence of a specific feature in a class is independent of the existence of any other feature. On applying text classification, each word in the input text is considered a feature, and the classifier calculates the likelihood of each label given the presence of these words, as portrayed in Figure 3.4.

To convert the textual data into a structure suitable for the classifier, we use the TF-IDF vectorization method. TF-IDF allocates weights to words depending on their frequency in each input text and across the dataset. Words that are common in an input text but rare in the rest of the dataset are considered important and receive higher weights. This helps in capturing the importance of each word in the input text.

Furthermore, to prepare the labels for the classifier, we use label encoding to convert categorical labels into numerical format, thus ensuring that the classifier can understand and process the labels correctly. The classifier is then trained on the TF-IDF transformed training data, where it learns the relationships between the input features (TF-IDF vectors) and the numerical target labels. Finally, the trained classifier is used to predict the labels for the validation dataset, and the accuracy of the model and other metrics are evaluated.

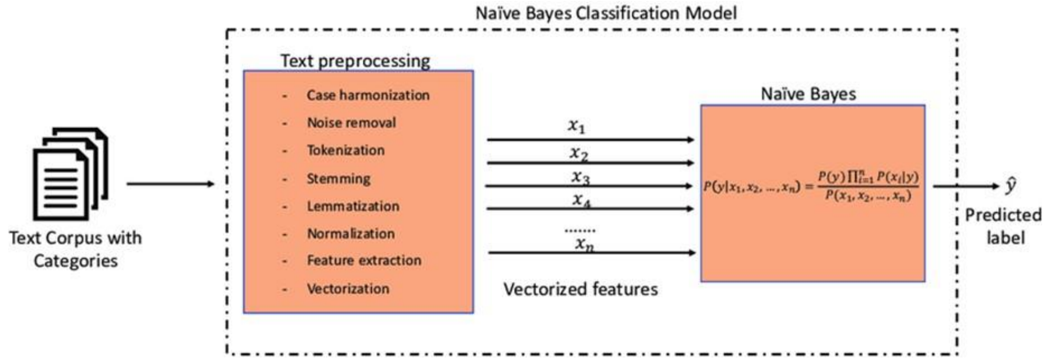

Figure 3.4: Naive Bayes Classification Model

3.6 SVM Architecture

The robust supervised machine learning algorithm Support Vector Machine (SVM) maps input textual information into a high-dimensional space. In this approach, each word becomes a feature. The algorithm then retrieves the optimal hyperplane as depicted in Figure 3.5, that best separates different classes, effectively classifying the input text into predefined categories.

In this project, we employ the 'svm.SVC' class from the scikit-learn library to create an SVM model with certain parameters. The regularization strength, which is responsible for achieving an impact on the trade-off between correctly classifying training points and achieving a smooth decision boundary is controlled by the C parameter and is set to 1.0. We implement a linear kernel to build a linear decision boundary for the separation of classes by a hyperplane.

The model is trained on TF-IDF (Term Frequency-Inverse Document Frequency) transformed training data, which represents each input text as a vector of TF-IDF scores. The training labels are used to fit the model, allowing it to discover the relationships between the labels and the input features.

Once the training phase is complete, the SVM model is used to predict labels for the test data. After comparing the model's predictions with the actual labels, the evaluation metrics determine how accurate the model is.

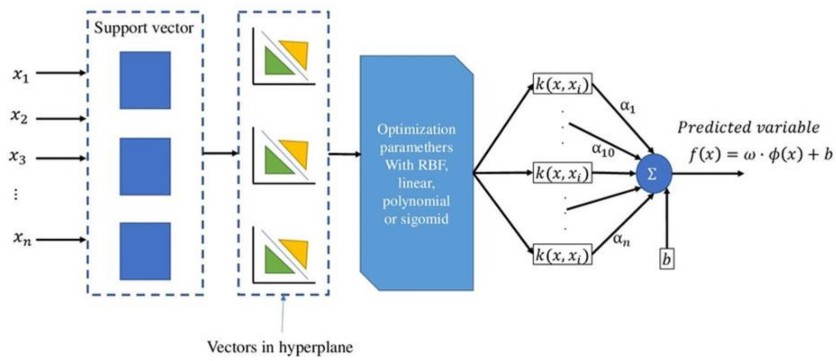

Figure 3.5: Support Vector Machines Model

3.7 RNN Architecture

The model architecture here utilizes a bidirectional GRU neural network (Gated Recurrent Unit) to classify input text data. The text data is first processed using the text vectorization layer, which labels the input text and converts it to numbers. These representations are then embedded in a dense vector space using embedding layers of dimension 64, as portrayed in Figure 3.6.

The core of the model consists of two bidirectional GRU layers. The first GRU layer has 64 units and returns sequences that allow capturing both forward and backward temporal dependencies. The resulting sequences are then passed to another bidirectional 32-unit GRU layer, which combines the data from both directions. After the recurrent layers, a 64-unit dense layer and the ReLU activation function are used to transform the features. Finally, a dense layer with one output neuron is added to generate binary classification protocols in sentiment analysis that indicate the probability that the estimate is positive or negative. The model is built using binary cross-entropy loss, Adam's optimization, and accuracy metrics.

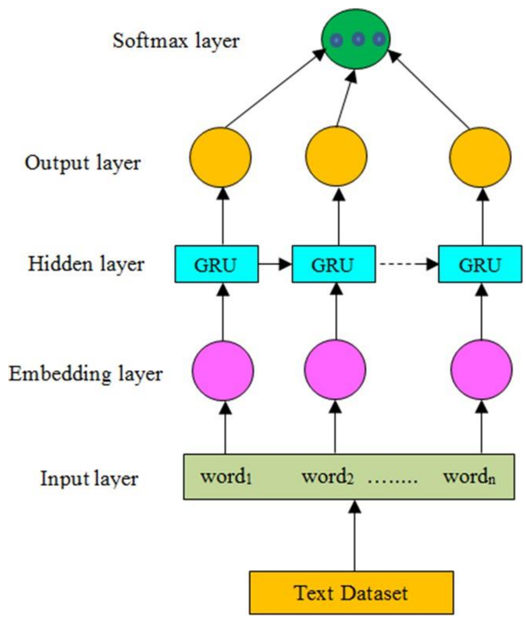

Figure 3.6: RNN Model

Chapter 4

Experiments

Zero-shot text classification as well as traditional supervised learning approaches are applied on the three datasets. We delve into the implementation of each approach on the datasets.

4.1 Zero-Shot Text Classification

In this approach, the facebook/bart-large-mnli model is implemented on the input text column of the three datasets. The model predicts the sentiment label by evaluating how well the input text entails the each candidate label. The sentiment label with the highest confidence score is portrayed as the predicted label for the input text. The predicted labels and ground truth labels are first converted into numerical format for ease of comparison. Evaluation metrics such as accuracy, F1-score, precision and recall are computed for comparison purposes.

4.2 Naive Bayes Classifier

The Multinomial Naive Bayes classifier is applied to the input text column of the three datasets. This input text is pre-processed through the tokenization, lowercasing and lemmatization steps. The pre-proceesed text is then converted into numerical features using TF-IDF vectorization. Subsequently, the sentiment labels are converted into a numerical format (0 for the negative text and 1 for the positive text). The NB classifier is then trained on the input text that has been transformed using TF-IDF, enabling it to grasp the probability distributions associated with each word concerning the sentiment labels. The likelihood of each sentiment label given the input text is calculated by the classifier which then chooses the most probable label. After taking both the predicted labels and the actual labels into comparison, the model's performance is then assessed employing metrics such as accuracy, precision, recall, and F1-score.

4.3 Support Vector Machines

In the case of SVM approach, all the terms of the given input text are used as features. This involves transforming the input text data into a multi-dimensional space and determining the appropriate plane for dividing the text data. During execution of the code, the 'svm.SVC' class from the scikit-learn library is used to represent an SVM model with specific parameters. A linear kernel is defined for separating the classes by the hyperplane. Subsequently, the model is trained on the training data that has been converted into TF-IDF format. This is done to learn the relationships between the input features and the corresponding labels. Following training, the SVM model predicts labels for the test data, and metrics such as accuracy and others are computed to analyse the performance of this model.

4.4 Recurring Neural Networks

The GRU variant of the RNN model is employed for text classification. The input text data is first preprocessed, which includes tokenization and vectorization. The dataset is then divided into training and testing sets. Subsequently, the model is constructed, comprising of a text vectorization layer to convert text into numerical form, an embedding layer to map the input text to dense vectors, and bidirectional GRU layers to capture both the past and future context in the text. The model is then compiled with an appropriate loss function and optimizer. The Binary Cross Entropy loss function aids in predicting the correct label by comparing the raw model predictions (logits) to the actual labels. It provides a measure of the difference between the predicted and actual probabilities, guiding the model to adjust its parameters for more accurate predictions. The Adam optimizer regulates how quickly the model learns from the data, thus enabling it to make better predictions. The significance of various data components is taken into account to accelerate learning in areas that require it most. Combined with the ability of the model not to be tuned to fit a particular input, this technique allows to determine the correct label for the input texts accurately. Finally, the evaluation metrics are computed to assess the performance of the constructed model.

Chapter 5

Results

This section includes the results of the four text classification approaches, displaying the evaluation metrics of the three datasets in a tabular format and providing visual representations of the results in the form of bar graph plots.

5.1 Amazon Reviews Dataset

	ZSL	Naive Bayes	SVM	RNN
Accuracy	0.92	0.83	0.87	0.86
F1 Score	0.91	0.83	0.87	0.85
Precision	0.95	0.83	0.87	0.86
Recall	0.88	0.83	0.87	0.84

Table 5.1: Amazon Reviews Dataset - Evaluation Metrics

ZSL achieves highest accuracy as depicted in Table 5.1, when compared to conventional methods like Naive Bayes, SVM and RNN, thus implying the strong foothold of this model in the field of text classification. Achieving a superb precision score of 0.95, ZSL makes sure that when it predicts a class label, it is often correct. ZSL's high accuracy and precision scores stem from its ability to generalize effectively across different categories without the necessity of explicitly being trained on specific samples, thus making it efficient when classes may be diverse and not well-defined. The Naive Bayes classifier, achieving an accuracy of 0.83, exhibits poorer performance in comparison to ZSL across all metrics. The reason for the decline in the metric scores could be attributed to its assumption of independence among features, which may not hold true for text data where the occurrence of words is interconnected. SVM and RNN perform similarly in terms of accuracy, precision, and recall, with SVM having slightly higher scores. Overall, these results suggest ZSL's ability to generalize and make accurate predictions without the need for labeled training samples, thus making it particularly well-suited for the Amazon Reviews dataset. A bar graph plot of the evaluation metrics are depicted in Figure 5.1 and Figure 5.2 for illustration purposes.

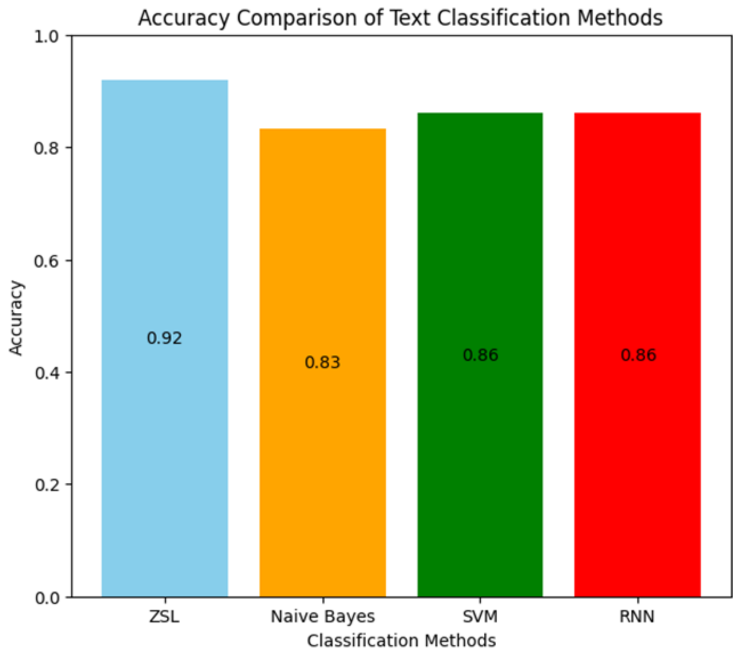

Figure 5.1: Accuracy Bar Graph Plot for Amazon Reviews Dataset

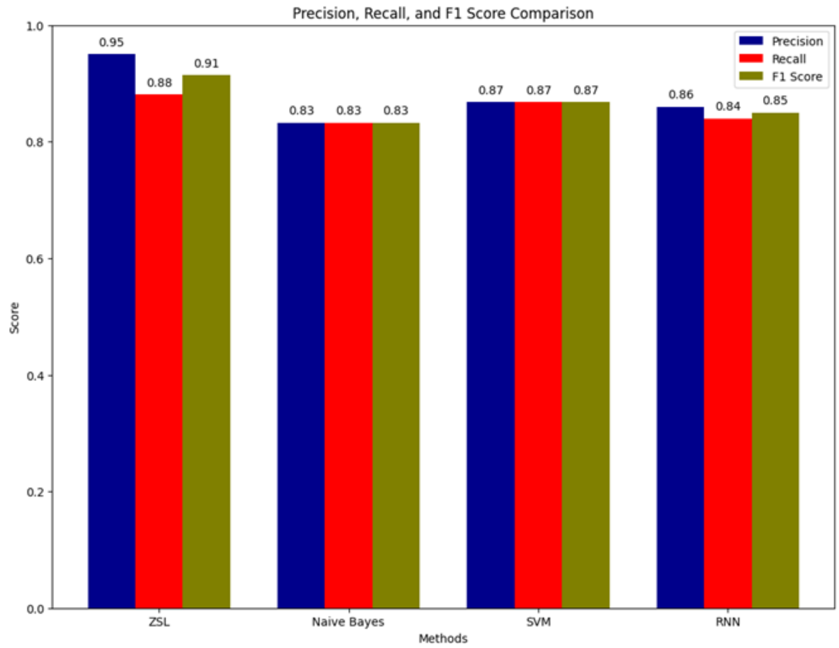

Figure 5.2: Precision, Recall and F1-Score Bar Graph Plot for Amazon Reviews Dataset

5.2 Twitter Sentiment Dataset

	ZSL	Naive Bayes	SVM	RNN
Accuracy	0.93	0.89	0.89	0.87
F1 Score	0.90	0.89	0.89	0.75
Precision	0.84	0.89	0.89	0.80
Recall	0.97	0.89	0.89	0.71

Table 5.2: Twitter Sentiment Dataset - Evaluation Metrics

In this dataset as well, ZSL demonstrates the highest accuracy of 0.93, as evident from Table 5.2, showcasing its effectiveness in making accurate predictions overall. ZSL also attains the highest recall score of 0.97, thus indicating its effectiveness in capturing a meaningful portion of relevant instances in the dataset, which is crucial for sentiment analysis on social media data. However, ZSL's precision score of 0.84 is lower compared to Naive Bayes and Support

Vector Machine (SVM), suggesting that while ZSL identifies many relevant instances, it has the tendency to generate more false positives. Naive Bayes and SVM, on the other hand, exhibit the same metric score of 0.89 across accuracy, precision, and recall and F1-scores. This implies that both Naive Bayes and SVM are well-suited for this dataset, after ZSL. Conversely, Recurrent Neural Network (RNN) has a slightly lower accuracy of 0.87 but poor performance in the other metrics. This highlights its shortcomings in capturing sentiment in brief social media tweets. Bar graphs in Figure 5.3 and Figure 5.4 present the distribution of evaluation metrics for the different text classification methods.

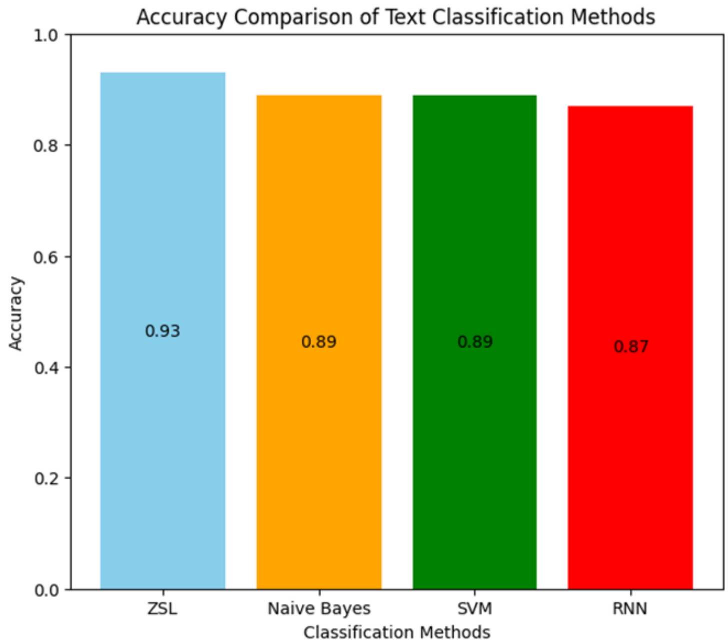

Figure 5.3: Accuracy Bar Graph Plot for Twitter Sentiment Dataset

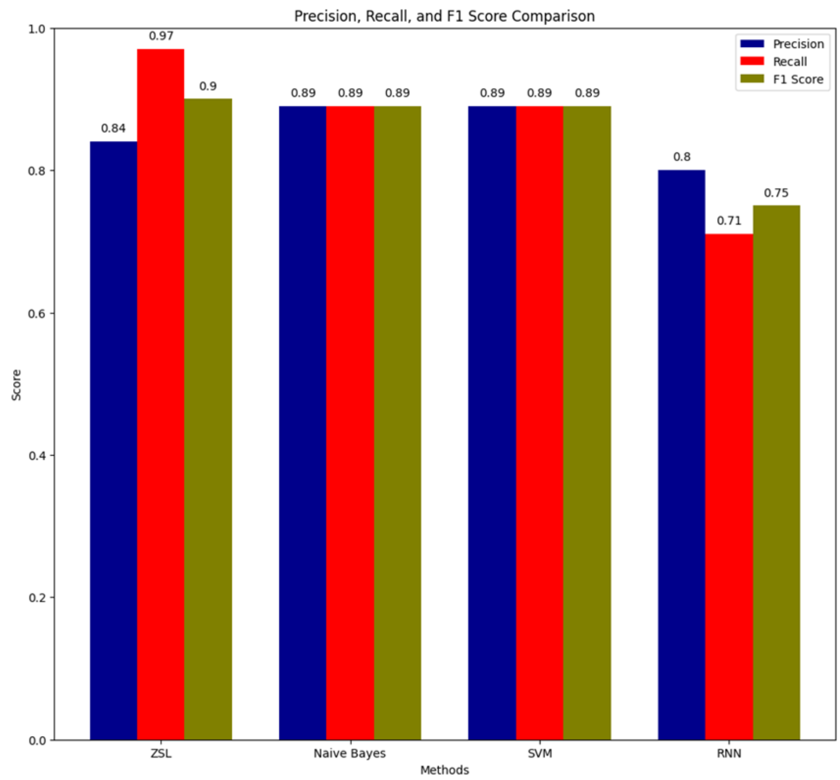

Figure 5.4: Precision, Recall and F1-Score Bar Graph Plot for Twitter Sentiment Dataset

5.3 Restaurant Reviews Dataset

	ZSL	Naive Bayes	SVM	RNN
Accuracy	0.98	0.83	0.79	0.78
F1 Score	0.98	0.82	0.79	0.77
Precision	0.97	0.83	0.80	0.78
Recall	0.98	0.81	0.79	0.80

Table 5.3: Restaurant Reviews Dataset - Evaluation Metrics

In this dataset, as shown in Table 5.3, Zero-Shot Learning (ZSL) demonstrates superior performance across all metrics on comparison with Naive Bayes, SVM, and RNN. The metric scores of ZSL in this dataset surpass those of the previous datasets. This impressive performance demonstrates that ZSL can effectively generalize among different categories without needing specific training examples, regardless of the text reviews being short and brief. In the case of Naive Bayes approach, the slightly lower disparity in the accuracy when compared to the ZSL model can be attributed to the inherent assumption of feature independence in Multinomial Na¨ıve Bayes. This assumption could not fully capture the complex linguistic patterns and context dependencies present in the natural language. SVM, on the other hand could not extract the features from the TF-IDF vectorization failing to fully capture their details. RNN's low performance suggests that, due to a smaller training dataset, the model has fewer examples to learn from, potentially leading to an overfitting generalization to unseen data. The bar graph plots of this dataset are shown in Figure 5.5 and Figure 5.6.

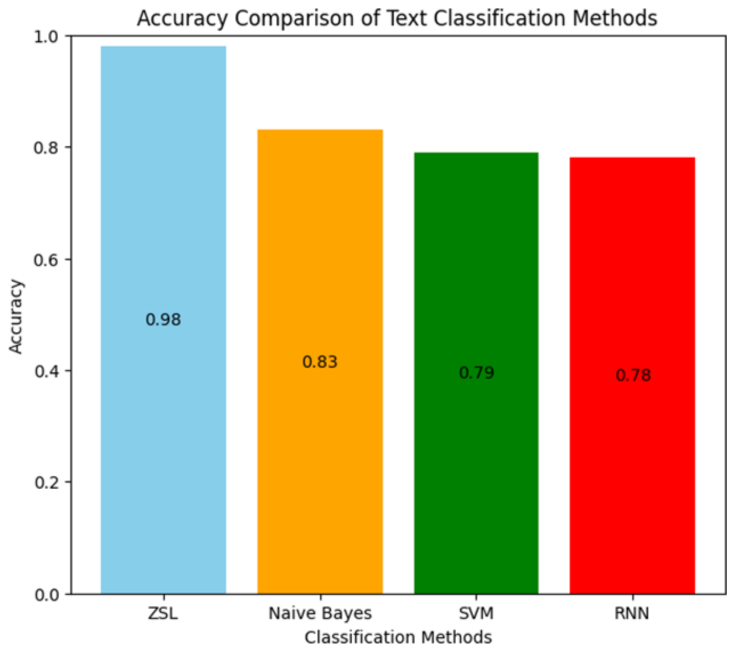

Figure 5.5: Accuracy Bar Graph Plot for Restaurant Reviews Dataset

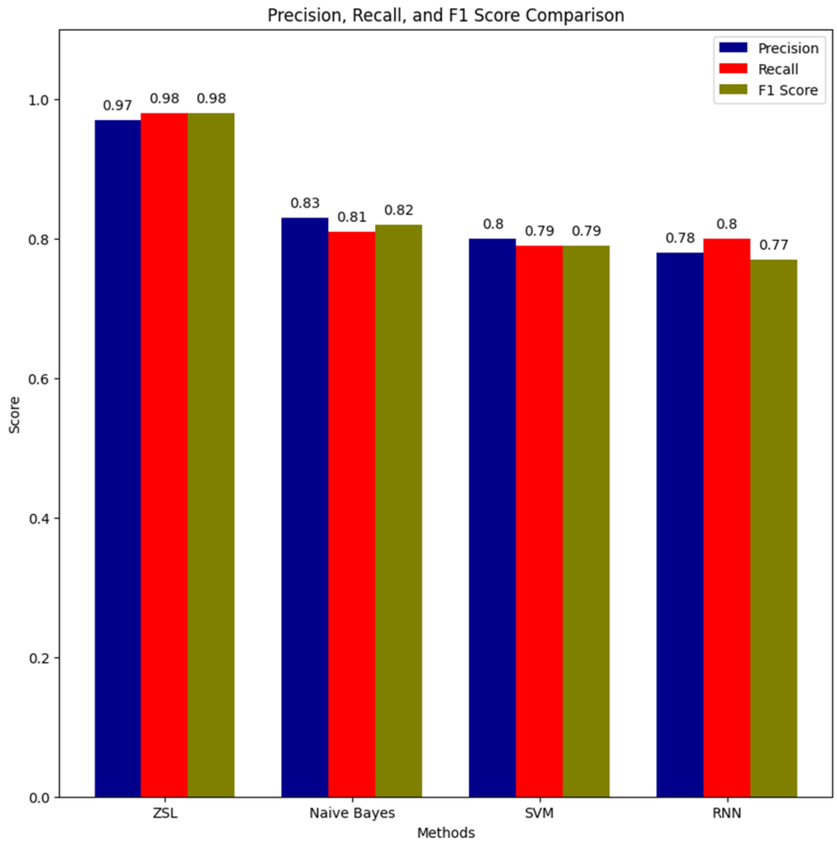

Figure 5.6: Precision, Recall and F1-Score Bar Graph Plot for Restaurant Reviews Dataset

Chapter 6

Conclusion and Future Scope

To summarize, our study into zero-shot text classification (ZSL) has shown great potential in tackling the problem of categorizing text into predefined categories without requiring explicit training on those categories. ZSL models like the transformer model facebook/bart-large-mnli, which make use of auxiliary information and semantic representations, have demonstrated extraordinary performance in text classification across a diverse range of datasets, irrespective of the text size and the number of input texts in each dataset. In addition to implementing ZSL to the Amazon Reviews dataset, Twitter sentiment prediction dataset and restaurant food review dataset, we have evaluated its effectiveness in conventional supervised text classification techniques comprising Naive Bayes, SVM, and RNN. ZSL's effectiveness is demonstrated by the emergence of high accuracy values of 0.92, 0.93 and 0.98, expressing its ability to easily generalize to new, unseen classes.

For future work, we propose applying the zero-shot text classification model to datasets with more than just binary labels, such as datasets with multiple sentiments or to categorize text into different labels. Additionally, we aim to investigate the speed and computation time of our models to optimize their efficiency, potentially by leveraging parallel processing or other optimization techniques. Integrating zero-shot and few-shot learning paradigms could further enhance performance across tasks with varying data availability. These efforts will contribute to enhancing the scalability and applicability of our models in various real-world applications.

6.1 Sustainable Development Goals

Zero-shot text classification can be leveraged to address some of the sustainable development goals (SDG).

6.1.1 SDG 3 – Good Health and Well-Being

Data can be sourced from social media posts, news articles, surveys, or public health reports. These sources contain a variety of opinions and discussions about healthcare initiatives and access to quality healthcare. Zero-shot text classification can be applied to classify the collected texts into positive and negative labels. By leveraging this model, the opinions and feedback could be taken to improve the services in the healthcare domain.

6.1.2 SDG 8 – Decent Work and Economic Growth

The data acquired from social media platforms, newspapers, and economic reports related to job creation, rising marking trends, unemployment, and job insecurity, provides an overview of problem areas that need to addressed and potential actions to improve job market conditions. For example, if there are many negative sentiments regarding job insecurity, policymakers and employers may consider measures to enhance job security and stability.

Appendices

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Table 6.1: Project Detail

Student Details

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Project Details

Project Title	Unveiling the Untapped Potential of Zero-Shot Text Classification		
Project Duration	4-6 Months	Date of Reporting	03-01-2024

Internal Guide Details

Faculty Name	Dr.Girija Attigeri		
Full Contact Address with PIN Code	Department of Information and Communication Technology, Manipal Institute of Technology, Manipal-576104		
Email Address	girija.attigeri@manipal.edu		

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How much of this submission has been generated by AI?

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Caution: Percentage may not indicate academic misconduct. Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Frequently Asked Questions

What does the percentage mean?

The percentage shown in the AI writing detection indicator and in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was generated by AI.

Our testing has found that there is a higher incidence of false positives when the percentage is less than 20. In order to reduce the likelihood of misinterpretation, the AI indicator will display an asterisk for percentages less than 20 to call attention to the fact that the score is less reliable.

However, the final decision on whether any misconduct has occurred rests with the reviewer/instructor. They should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in greater detail according to their school's policies.

How does Turnitin's indicator address false positives?

Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be AI-generated will be highlighted blue on the submission text.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

What does 'qualifying text' mean?

Sometimes false positives (incorrectly flagging human-written text as AI-generated), can include lists without a lot of structural variation, text that literally repeats itself, or text that has been paraphrased without developing new ideas. If our indicator shows a higher amount of AI writing in such text, we advise you to take that into consideration when looking at the percentage indicated.

In a longer document with a mix of authentic writing and AI generated text, it can be difficult to exactly determine where the AI writing begins and original writing ends, but our model should give you a reliable guide to start conversations with the submitting student.

CO and PO Mapping

*[The COs for project work and the UG POs and PSOs are listed below. With respect to your project, map the COs to the POs and PSO's with the correlation levels as below **in consultation with your college guide:**
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2 (if the CO has MODERATE EMPHASIS to the POs and PSOs)
1 (if the CO has LOW EMPHASIS to the POs and PSOs)
Put '–' (hyphen) if the CO is not related to the POs and PSOs]

CLOs		PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
ICT 4299.1	Assess the work available in the literature related to the project to identify the limitations and risks.	2	3	2	2	2	1	1	-	2	1	1	2
ICT 4299.2	Practice planning and time management in solving the problem.	2	2	2	1	1	-	-	1	1	2	1	2
ICT 4299.3	Demonstrate professional skills to work effectively in a team or individually.	1	1	2	1	1	-	-	1	3	3	2	2
ICT 4299.4	Develop the ability to adopt a methodological approach to solve societal problems..	2	2	2	3	2	2	3	2	1	1	2	3
ICT 4299.5	Conduct experimentation and testing to achieve the defined objectives through computing/coding/statistical analysis	3	2	3	3	3	1	1	-	1	1	2	2
ICT 4299.6	Compose the technical report with effective communication on incorporating ethical practices.	1	1	1	1	1	2	2	3	2	3	2	1
ICT 4299 (Avg. correlation level)		**1.83**	**1.83**	**2**	**1.83**	**1.66**	**1**	**1.16**	**1.16**	**1.66**	**1.83**	**1.66**	**2**

PROGRAM OUTCOMES (PO)

Engineering Graduates will be able to:
1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one’s own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

CLOs		PSO1	PSO2	PSO3	PSO4	PSO5	PSO6	PSO7	PSO8	PSO9
ICT 4299.1	Assess the work available in the literature related to the project to identify the limitations and risks.	3	3	2	1	1	-	-	-	-
ICT 4299.2	Practice planning and time management in solving the problem.	2	2	2	1	1	1	-	-	1
ICT 4299.3	Demonstrate professional skills to work effectively in a team or individually.	2	2	2	1	1	-	-	1	2
ICT 4299.4	Develop the ability to adopt a methodological approach to solve societal problems..	2	2	2	2	2	2	3	2	2
ICT 4299.5	Conduct experimentation and testing to achieve the defined objectives through computing/coding/statistical analysis	3	3	3	2	3	1	1	1	1
ICT 4299.6	Compose the technical report with effective communication on incorporating ethical practices.	2	2	1	1	1	2	2	2	2
ICT 4299 (Avg. correlation level)		**2.33**	**2.33**	**2**	**1.33**	**1.5**	**1**	**1**	**1**	**1.33**

1. To identify, analyse and develop software systems using appropriate techniques and concepts related to information technology
2. To design an algorithm or process within realistic constraints to meet the desired needs through analytical, logical and problem-solving skills.
3. To apply state of the art IT tools and technologies, IT infrastructure management abilities in treading innovative career path as a prospective IT engineer
4. Apply the principles of science, maths and computer programming to solve complex problems related to information technology.
5. Apply knowledge of programming, computational intelligence, computer graphics and visualization, data analytics, software system design, cyber security to arrive at solutions to real world problems.
6. Apply IT knowledge to design and develop systems with respect to societal, user, customer needs, health and safety, diversity, inclusion, societal, environmental codes of practise and industry standard.
7. Integrate and interface industry relevant hardware and software components and technology to come up with innovative and creative solutions.
8. Use of industry standard software tools and platform to design and analyze IT systems.
9. Learn to function collaboratively as a member of leader in diverse teams in multidisciplinary settings to manage the process effectively and document, present and communicate with the engineering community.

COURSE Code	Course Title	PO 1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
ICT 4299	Project Work	**1.83**	**1.83**	**2**	**1.83**	**1.66**	**1**	**1.16**	**1.16**	**1.66**	**1.83**	**1.66**	**2**

COURSE Code	Course Title	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6	PSO7	PSO8	PSO9
ICT 4299	Project Work	**2.33**	**2.33**	**2**	**1.33**	**1.5**	**1**	**1**	**1**	**1.33**

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2 (if the CLO has MODERATE EMPHASIS to the AHEP LO)

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Put '–' (hyphen) if the CLO is not related to the AHEP LO

Note: Make sure that all columns shown will have at least one entry.]

CLOs		**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C13**	**C16**	**C17**
ICT 4299.1	Assess the work available in the literature related to the project to identify the limitations and risks.	3	3	2	3	-	-	2	1	2
ICT 4299.2	Practice planning and time management in solving the problem.	2	2	1	1	-	-	1	1	-
ICT 4299.3	Demonstrate professional skills to work effectively in a team or individually.	-	-	1	2	1	2	1	2	1
ICT 4299.4	Develop the ability to adopt a methodological approach to solve societal problems..	2	2	-	2	3	2	3	2	1
ICT 4299.5	Conduct experimentation and testing to achieve the defined objectives through computing/coding/statistical analysis	3	3	3	3	2	1	-	-	2
ICT 4299.6	Compose the technical report with effective communication on incorporating ethical practices.	1	-	-	1	1	2	2	3	2
ICT 4299 (Avg. correlation level)		**1.83**	**1.66**	**1.16**	**2**	**1.16**	**1.16**	**1.5**	**1.5**	**1.33**

Category	AHEP LO number	AHEP LO Statements
Science & Maths	C1	Apply knowledge of mathematics, statistics, natural science and engineering principles to the solution of complex problems. Some of the knowledge will be at the forefront of the particular subject of study
Engineering Analysis	C2	Analyse complex problems to reach substantiated conclusions using first principles of mathematics, statistics, natural science and engineering principles
	C3	Select and apply appropriate computational and analytical techniques to model complex problems, recognising the limitations of the techniques employed
	C4	Select and evaluate technical literature and other sources of information to address complex problems
Design & Innovation	C5	Design solutions for complex problems that meet a combination of societal, user, business and customer needs as appropriate. This will involve consideration of applicable health & safety, diversity, inclusion, cultural, societal, environmental and commercial matters, codes of practice and industry standards
	C6	Apply an integrated or systems approach to the solution of complex problems
The Engineer & Society	C7	Evaluate the environmental and societal impact of solutions to complex problems and minimise adverse impacts
	C8	Identify and analyse ethical concerns and make reasoned ethical choices informed by professional codes of conduct
	C9	Use a risk management process to identify, evaluate and mitigate risks (the effects of uncertainty) associated with a particular project or activity
	C10	Adopt a holistic and proportionate approach to the mitigation of security risks
	C11	Adopt an inclusive approach to engineering practice and recognise the responsibilities, benefits and importance of supporting equality, diversity and inclusion
Engineering Practice	C12	Use practical laboratory and workshop skills to investigate complex problems
	C13	Select and apply appropriate materials, equipment, engineering technologies and processes, recognising their limitations
	C14	Discuss the role of quality management systems and continuous improvement in the context of complex problems
	C15	Apply knowledge of engineering management principles, commercial context, project and change management, and relevant legal matters including intellectual property rights
	C16	Function effectively as an individual, and as a member or leader of a team
	C17	Communicate effectively on complex engineering matters with technical and non-technical audiences
	C18	Plan and record self-learning and development as the foundation for lifelong learning/CPD