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Food Review Analysis Using Zero Shot Learning

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ABSTRACT:We live in a digitized era where our daily life depends on using online resources. Businesses consider the opinions of their customers, while people rely on the reviews/comments of other users before buying specific products or services. These reviews/comments are usually provided in the non-normative natural language within different contexts and domains (in social media, forums, news, blogs, etc.). Sentiment classification plays an important role in analyzing such texts collected from users by assigning positive, negative, and sometimes neutral sentiment values to each of them. Moreover, these texts typically contain many expressed or hidden emotions (such as happiness, sadness, etc.) that could contribute significantly to identifying sentiments. We address the emotion detection problem as part of the sentiment analysis task. Zero-shot learning involves using pre-trained language models, such as BART, to perform tasks for which they have not been specifically trained. BART can be fine-tuned for various natural language processing tasks, including MNLI and Multi-lingual NLI. The model learns to encode the meaning of sentences, allowing it to make accurate inferences about their relationships. Zero-shot learning with BART is useful in situations where labelled data is scarce or expensive to obtain.

KEYWORDS:Sentiment analysis, Emotion detection, Sentence transformers, Zero-shot model, ensemble learning, Natural language inference.

I. INTRODUCTION

For many years, humans have had to adjust their communication style to be ‘understood’ by computers, but communication in natural language has recently become a new trend. Huge amounts of texts available online are in the unstructured/unannotated form and therefore do not have much value. Such noisy data can be converted into useful information only after proper processing. However, manual processing is a cumbersome and time-consuming process. In contrast, the automatic techniques can help save manual labor, get the result faster, filter through huge amounts of unnecessary data to find appropriate material, and deliver the machine output in the desired format. Natural language

processing (NLP) tackles language technology problems by employing Artificial Intelligence (AI) methods for intelligent human-machine interaction. The AI technologies that use data mining, pattern recognition, and NLP, the computer can mimic the way the human brain works. NLP applications, such as machine translation systems, web search engines, natural language assistants, and opinion analysis, are resolving societal problems. Today, the mood (sentiments, emotions) of texts is

as important as their content. Sentiment and emotion detection plays a crucial role in analyzing social moods. Explosive social media growth enables users to share their opinions more and more and leave feedback online; this, in turn, makes Sentiment analysis become a powerful NLP tool able to analyze these texts automatically, helping companies/service providers to respond quickly and adequately. However, it can also be misused for spreading disinformation and hate speech, which can be detected automatically using sentiment analysis methods. Moreover, sentiment analysis even allows tracking of trends in real time by monitoring the popularity of products/services and even political candidates; and forecasting voting results. Here we focus on automatic sentiment analysis as one of the popular NLP problems that have found many areas of applications by analyzing customers' product reviews, social media, survey unstructured responses, etc. The goal of sentiment analysis is to analyze, generalize, and predict whether the text contains subjectivity and expresses the sentiment, apart from which sentiment is the dominant. Most sentiment analysis studies focus on assigning positive, negative, and sometimes neutral sentiment values to the given text. A less studied direction in sentiment analysis is to move the aim from analyzing sentiment toward a specific item to the internal mood of the text itself.

Zero-shot cross-lingual experiments present the evaluation of monolingual models applied to another language. Most models function well with commonly used languages such as English; however, applying these algorithms straight to low-quality corpora frequently yields disappointing results. Cross-lingual sentiment analysis aims to employ high quality and rich resources in English to improve the classification performance of resource scarce languages. These methods address the problem of training separate models for each language, but despite that, they lack mechanisms able to modify traditional training methods (classifiers) for the Sentiment analysis task. To our current knowledge, emotion detection and sentiment classification are two different tasks that are often solved independently. However, in this project, we assume that the sentiment analysis problem can be tackled more effectively if we rely on emotion detection first.

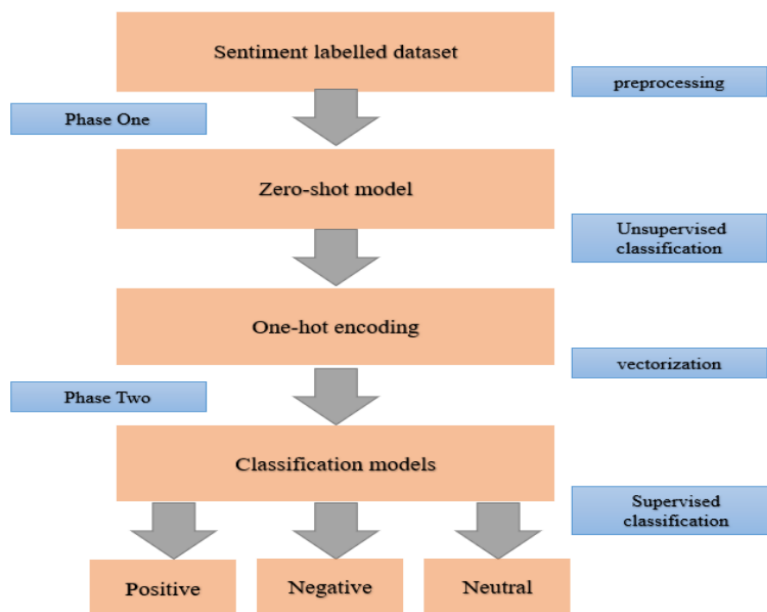
II. RELATED WORK

Sentiment analysis is among the principal tasks of NLP that strives to predict opinion polarity. It often predicts the sentiment as belonging to one of the three categories (negative, neutral and positive) that can be used in many areas such as customer product review, political forecasting, telehealth services, finance. According to Medhat et al, we describe the taxonomy of sentiment analysis techniques and divide it into two main paradigms: rule-/lexicon-based and machine learning. Lexicon-based methods rely on the assumption that the overall sentiment depends on the words that explicitly express these sentiments. Words (adjectives, adverbs, sometimes verbs, and nouns) that define different sentiments are searched in the text and counted: the overall sentiment of the text depends on the majority. In machine learning, the sentiment analysis task is typically formulated as the text classification task and, therefore, can be solved with a whole spectrum of methods for this purpose: traditional machine learning methods (e.g., Support Vector Machine (SVM)), deep learning methods (e.g., Long Short-term Memory (LSTM), Convolutional Neural Network (CNN)), or innovative sentence transformer models (e.g., Bidirectional Encoder Representation from Transformer (BERT)). For many years different languages were treated separately by training monolingual models from scratch for separate tasks and separate languages. Recently, many pre-trained models provided by open-source NLP libraries, such as BERT and NTLK, were introduced to minimize the efforts and resources required to learn general knowledge about the language and its structure (i.e., existing words, their meanings, and similarities). These transformer models are typically trained on very large monolingual or multilingual unannotated corpora (i.e., on pure texts) in a self-supervised manner and therefore are not adjusted for specific NLP problems. With the help of transfer learning, the previously acquired general knowledge in the pre-trained word- or sentence-transformer models can be augmented and fine-tuned to tackle the specific NLP problems (including the sentiment analysis task). Once the model is already 'familiar' with the language, it is much easier to adapt it to a specific NLP task: that is, typically, fewer training data are needed. Moreover, some multilingual transformer models are trained on the parallel corpora and tuned for similar tasks in the way they can cross barriers between languages. Cross-lingual methods have recently received more NLP community attention, thus demonstrated promising results when fine-tuned augmented transformer layers on different languages than they are later tested on (a good example is a group of the cross-lingual language model (XLM) transformers) Pre-



trained transformer models can be used for sentiment analysis tasks in very different manners: as text classifiers for the evaluation (by calculating distances between the unseen texts and texts of which the sentiments are already known); as zero-shot models that can evaluate the relatedness of some word (category, narrative, etc.) with the text. Zero-shot models can act as advanced dictionary-based methods that seek emotion or sentiment words both explicitly and implicitly and return probabilities determining how much these words are related to the text. The zero-shot models do not require the training data, but they are not directly adjusted for the sentiment analysis tasks and, therefore, may need additional mechanisms to go their limitations.

III. METHODOLOGY



The proposed two-stage method combines unsupervised and supervised machine learning paradigms in one pipeline. The core of the first stage is the pre-trained zero-shot model, which is applied to the emotion labels and the inputted text vectorized with the sentence transformer. The output of the zero-shot model is a list of emotion labels mapped to their probabilities for the input text. This output becomes an input into the second stage emotion probabilities are converted into a one-hot encoding format and then fed into the sentiment classifier trained to detect positive/negative/neutral (three-class classification scenario) or positive/negative (binary classification scenario) sentiments. For classification, we have used supervised machine learning methods, including neural networks and ensemble learning.

Pre-training BART: BART is pre-trained on a large corpus of text data using a language modelling task, where it learns to predict masked words in sentences, among other tasks. This helps BART to learn general language representations.

- Fine-tuning on MNLI and Multi-lingual NLI: BART is then fine-tuned on specific natural language inference tasks, such as MNLI and Multi-lingual NLI. During fine-tuning, BART is provided with labeled examples of sentence pairs and their corresponding relationships (e.g., entailment, contradiction, or neutral), and it adjusts its parameters to better predict the correct relationships based on the provided labels.
- Encoding Input Sentences: Once BART is fine-tuned, it can be used for zero-shot learning. To do this, input sentences are encoded using BART's encoder. The input sentences and target labels (e.g., positive or negative sentiment) are typically concatenated with a special separator token, forming a single input sequence.
- Relationship Inference: BART's encoder generates an output encoding for the concatenated input sequence. This encoding can be compared to predefined output encodings that correspond to different possible relationships (e.g., positive or negative sentiment) using similarity measures like cosine similarity or dot product. The relationship with the highest similarity score is predicted as the inferred relationship for the input sentence.
- Prediction and Evaluation: The predicted relationship can be used for the intended task, such as sentiment analysis or



other inference tasks. The accuracy or performance of the zero-shot learning approach can be evaluated using appropriate metrics, such as accuracy, F1 score, or other task-specific metrics.

IV. EXPERIMENTAL RESULTS

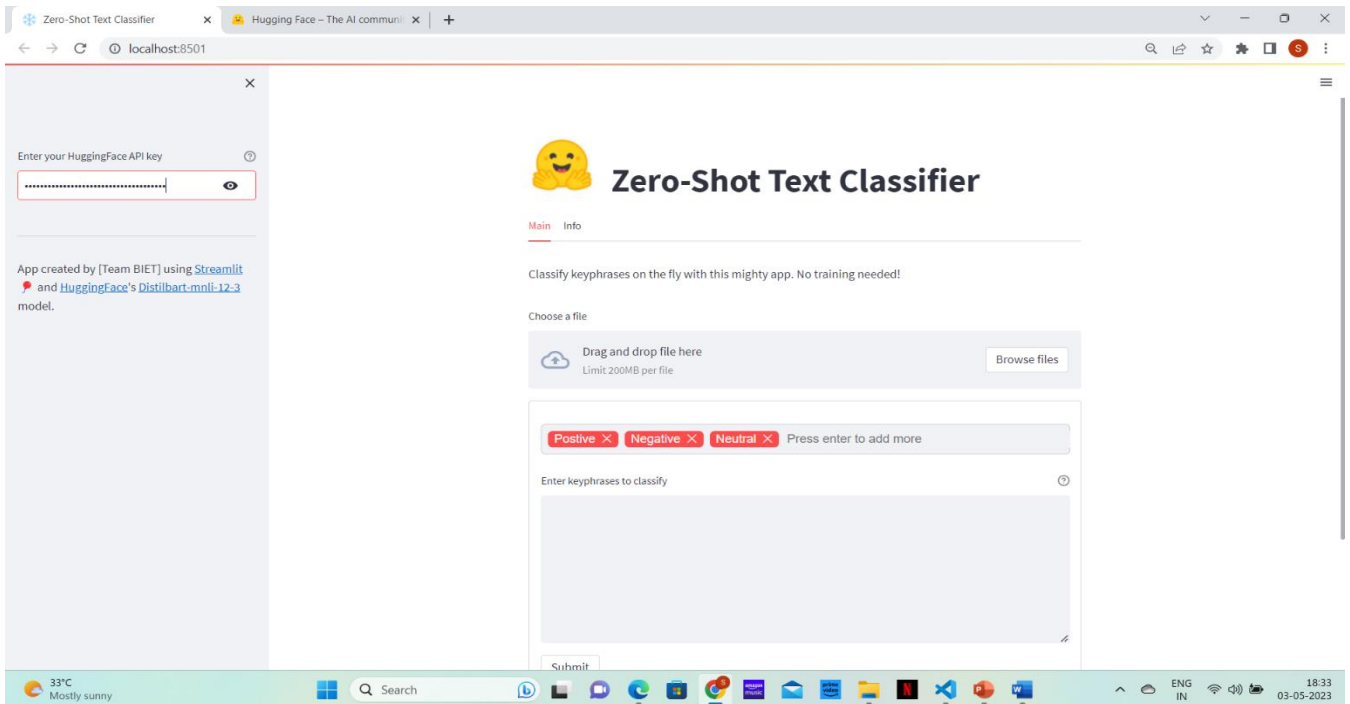


Fig.1 Home Page

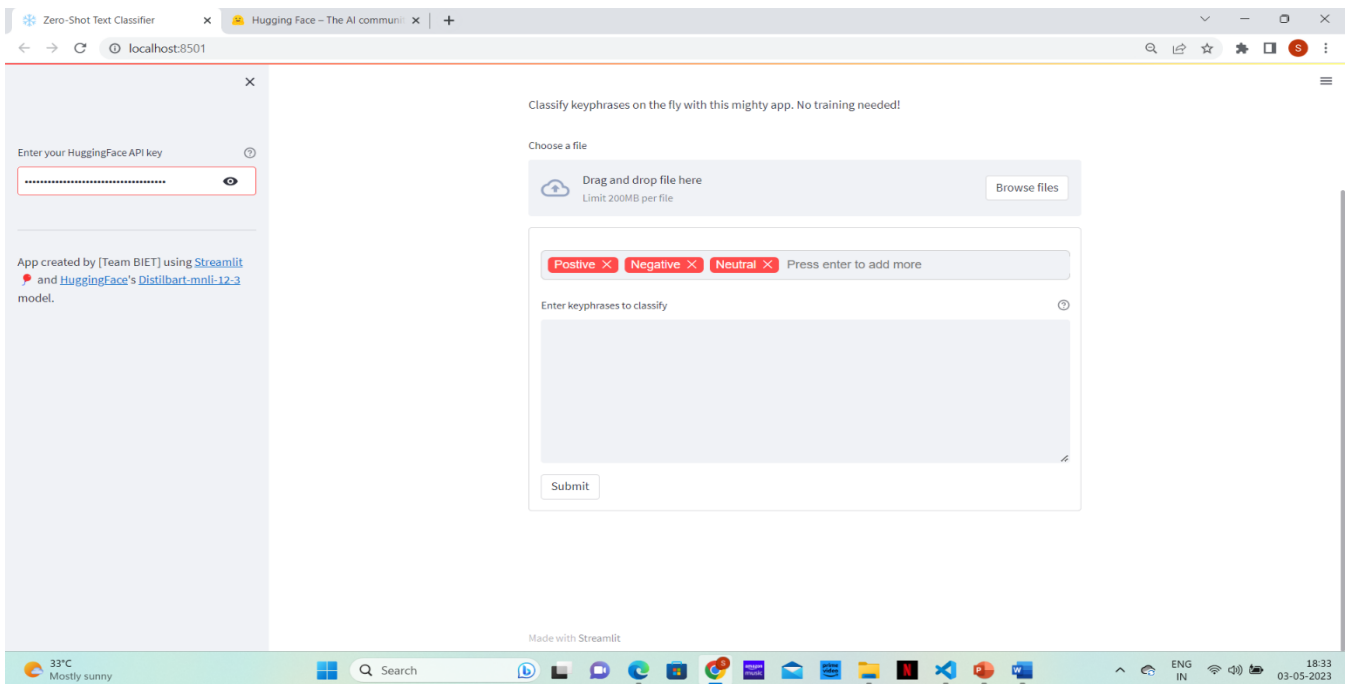


Fig.2 Home Page



Figure 1 and 2 depicts website's home page additionally it displays the API key needed to run the website as well as the labels provided in order to obtain the output.

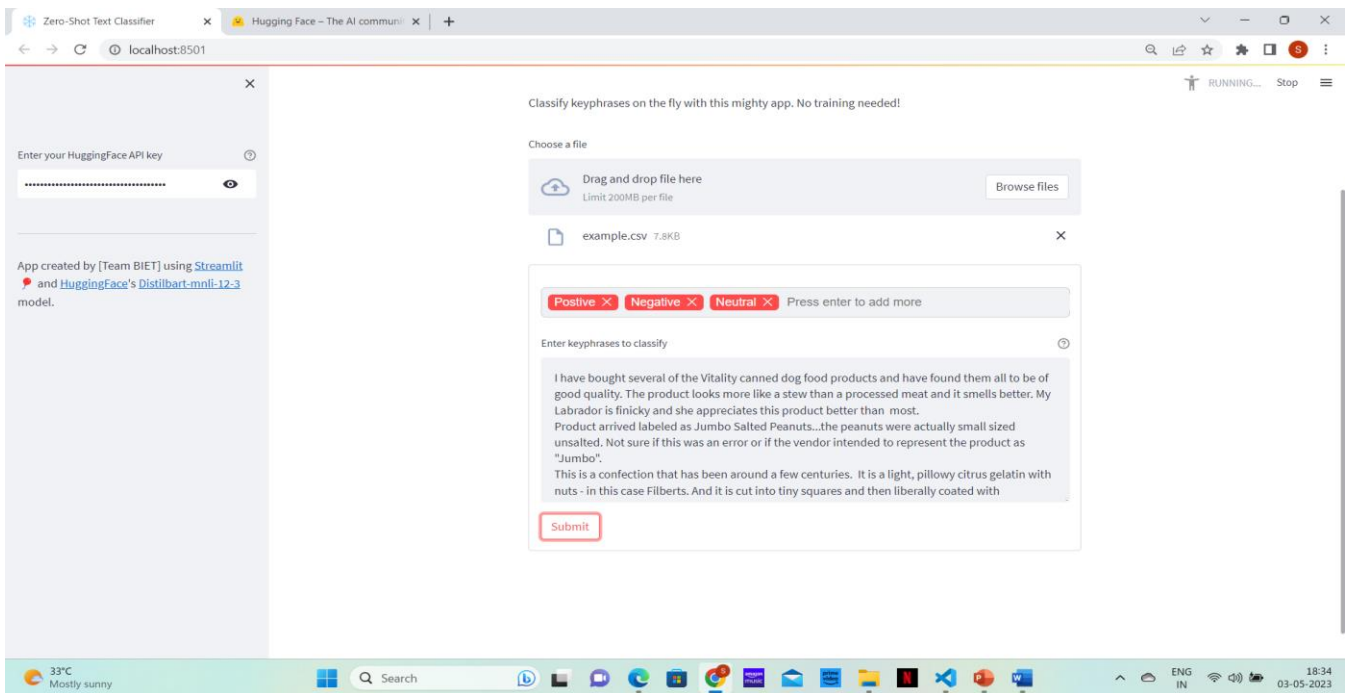


Fig.3 Uploading Input

Figure 3 illustrates the submitted input using the uploading feature to obtain the results.

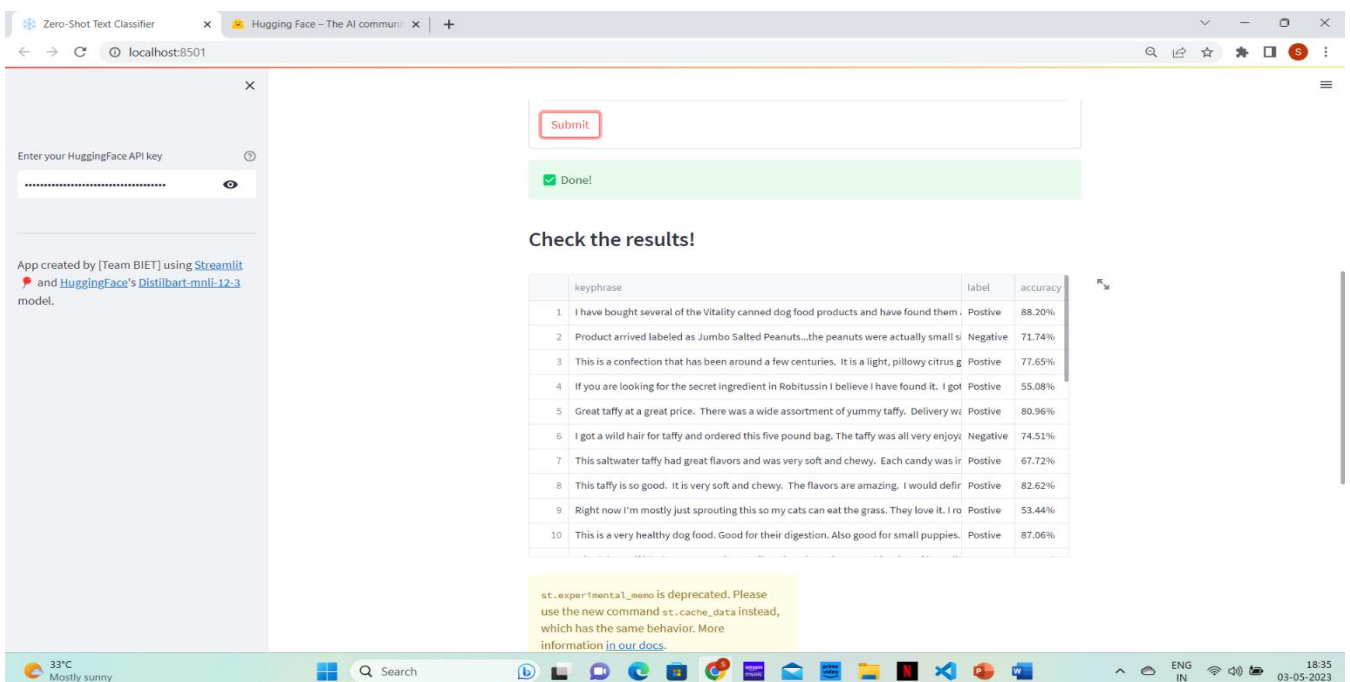


Fig.4 Results of specified input

Figure 4 displays the input results with the labels provided above and also displays the accuracy.

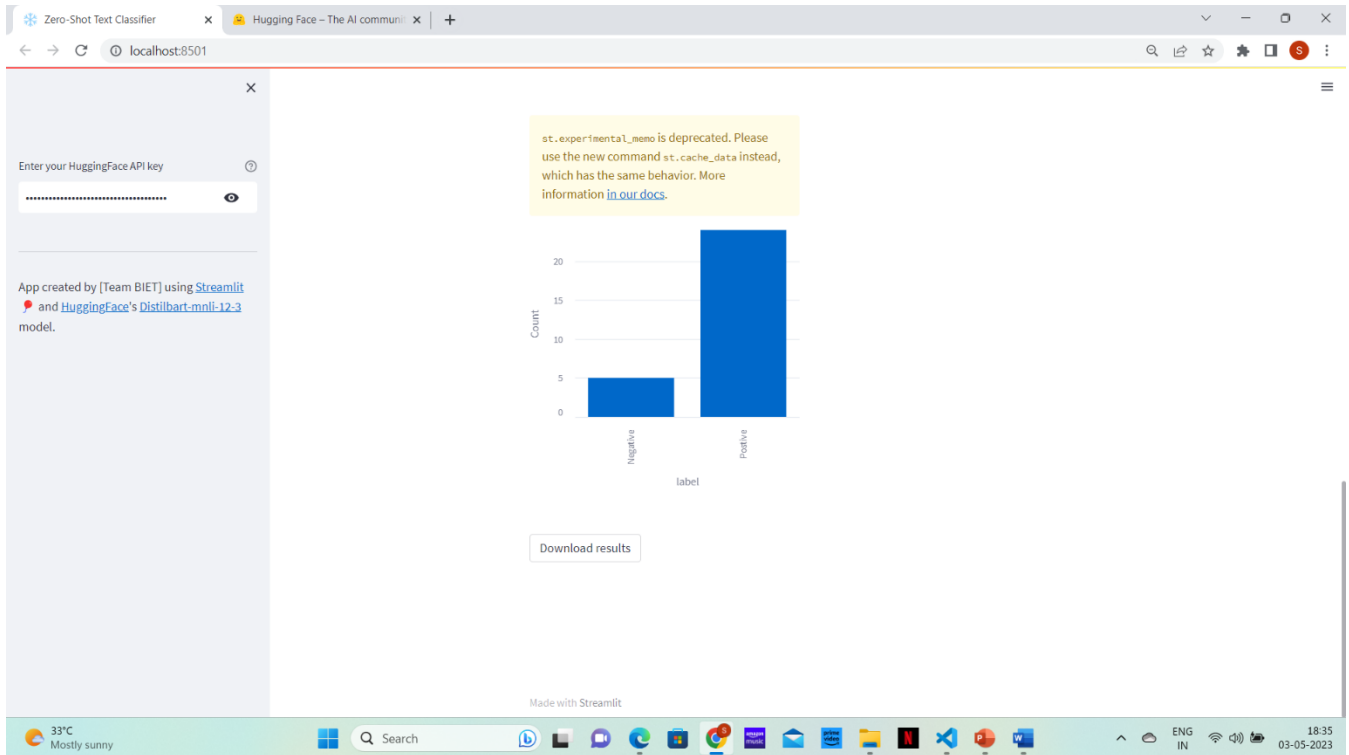


Fig.5 Displaying output in graphical representation

Figure 5 shows the results graphically

V. CONCLUSION

Zero-shot learning is a promising approach to machine learning that allows models to generalize to new, previously unseen tasks or classes without being explicitly trained on them. It involves learning a mapping between high-level concepts and lower-level features or attributes, which can be used to classify new instances of these concepts. One of the main advantages of zero-shot learning is that it can save time and resources by eliminating the need for extensive labeled training data for every new task. Instead, it leverages existing knowledge and semantic relationships to make accurate predictions about new classes. Multilingual model can perform natural language inference (NLI) on 100+ languages and is therefore also suitable for multilingual zero-shot classification. The main advantage of distilled models is that they are smaller, faster inference, lower memory requirements. While zero-shot learning is still an active area of research, it shows great potential for enabling more flexible and adaptable machine learning systems that can learn and generalize in a more human-like way. As the field continues to develop, we can expect to see more applications of zero-shot learning in areas such as natural language processing, computer vision, and robotics.

REFERENCES

1. Sagnika, S.; Pattanaik, A.; Mishra, B.S.P.; Meher, S.K. A review on multi-lingual sentiment analysis by machine learning methods. *J. Eng. Sci. Technol. Rev.* 2020, 13, 154–166.
2. Acheampong, F.A.; Nunoo-Mensah, H.; Chen, W. Transformer models for text-based emotion detection: A review of BERT-based approaches. *Artif. Intell. Rev.* 2021, 54, 5789–5829.
3. Kanclerz, K.; Milkowski, P.; Kocon, J. Cross-lingual deep neural transfer learning in sentiment analysis. *Procedia Comput. Sci.* 2020, 176, 128–137.



4. Mutanov, G.; Karyukin, V.; Mamykova, Z. Multi-class sentiment analysis of social media data with machine learning algorithms. *Comput. Mater. Contin.* 2021, 69, 913–930.
5. Krishnan, H.; Elayidom, M.S.; Santhanakrishnan, T. A comprehensive survey on sentiment analysis in twitter data. *Int. J. Distrib. Syst. Technol.* 2022, 13, 52.



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