

Improving Emotion Detection through Translation of Text to ML Models Trained in Different Languages

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Abstract

This Qualifying Exam¹ research paper investigates enhancing Emotion Detection (ED) by translating extended text data into various Machine Learning (ML) models trained in distinct languages. We focused on English and German text data to enhance prediction accuracy, aiming to overcome challenges arising from limited labeled datasets and language fragmentation in ED research.

Expanding an original English dataset with translated German data increases the training data's volume, potentially improving prediction rates in ED applications. Additionally, translating English to German to extend the German dataset and accessing in real-time ML models trained in both could further improve prediction rates.

For presentation purposes, datasets in both English and German were collected, parsed, cleaned, and translated. Multiple ML models trained in English and German were built, and made accessible via an API for predictions in either language including real-time translation using a GET method.

The research findings suggest that the extension of datasets through translation has not yielded improvements in predictive accuracy for both English and German languages. Modest enhancements could potentially be achieved by concurrently accessing English and German models through real-time translation via the RESTful API; however, the benefits may not fully justify the efforts.

We posit that the prevalence of numerous classes in this multi-class classification model has contributed to instances of overfitting across several labels/classes. This occurrence, in turn, has led to a memorization effect rather than facilitating genuine learning within the models.

In conclusion, it becomes evident that a more substantial accumulation of data is required, or an innovative approach involving the utilization of AI to generate analogous data must be employed to comprehensively address this research question.

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1 Introduction

Emotion detection (ED) has gained significant interest and investment[15] in recent years as a means to understand human behavior and improve communication effectiveness. By analyzing text, speech or facial expressions, these detection processes try to accurately identify and classify emotions expressed by individuals or groups, often in real-time.

By employing a variety of ED processes, including natural language processing (NLP) and machine learning (ML), applications with the right amount of data can detect emotions with high precision[2]. These ED systems find applications in diverse fields, such as sentiment analysis, customer feedback analysis, voting and news stance prediction, and mental health monitoring, which all aim at contributing to a deeper understanding of human emotions and their impact on various aspects of life.

1.1 Human Emotion as a Theoretical Framework

The concept and number of emotions can vary depending on the theoretical framework or model being considered. One well-known model is the Plutchik’s Wheel of Emotions seen in Figure 1, which proposes eight (8) primary emotions and their contrasting pairs. In this research paper we will be focusing on the basic eight (8) emotions and not on their sub-emotions or contrasting pairs. This allows the ML models being trained and built to be a multi-class classification model with eight labeled options.

The following are the eight primary emotions according to the Plutchik’s Wheel of Emotions [19] that we will be focusing on both in our English and German datasets. A detailed reference of emotions used in this research can be found in Table 2 on page 10.

- Happiness: A feeling of Joy (Fun), contentment, or delight.
- Sadness: A state of unhappiness, sorrow, or grief.
- Anger: An intense emotional response associated with feelings of displeasure, frustration, or hostility.
- Worry: An emotional response triggered by perceived threats or danger, often associated with anxiety or terror.
- Surprise: A sudden and unexpected reaction to something unusual or startling.
- Disgust and/or Hate: A strong aversion or revulsion towards something unpleasant, offensive, or repulsive.
- Trust and/or Love: A sense of reliance, confidence, or faith in someone or something.
- Enthusiasm: A feeling of excited expectation or eagerness towards future events.

It’s important to note that emotions are complex and multifaceted, and different emotion models and/or frameworks may propose alternative categorizations or variations in the number of primary

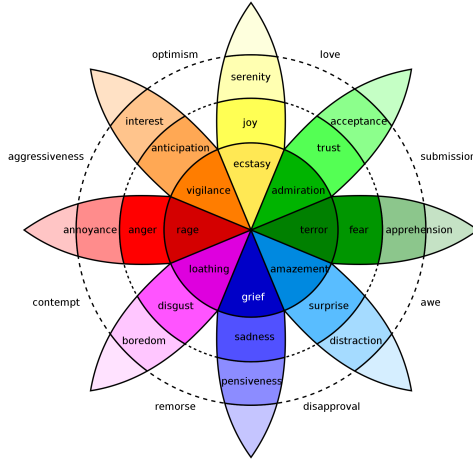


Figure 1: Plutchik Wheel of Emotions

emotions. However for the scope of this research project the most common eight (8) emotions are used as described above. This allows the ML models being trained and built to be a multi-class classification model with eight labeled classes.

By aligning the emotional labels across the English [6] and German [22] datasets that are being used in this research all eight listed above were linked to each other. Details on the linkage of the two datasets and their counts from data are described in Section 3.1 with an emphasis on Table 2’s cross reference on page 10 of German and English language data.

1.2 Significance of Emotion Detection in Machine Learning

Emotion Detection (ED) analysis in Machine Learning (ML) models has gained significant attention due to its potential applications in various fields, including customer sentiment analysis, stance detection in regard to a specific targets such as news and voting[10], mental health monitoring[4], and human-computer interactions such as chat-bots[1] to just name a few.

By accurately identifying and understanding emotions from text data, ML applications can assist in improving user experiences, decision-making processes, and overall human-machine interactions in a positive manner[4, 10], with most of these interactions being processed in real-time.

As an example, the primary goals of chat-bots are entertainment, social contact, support, and novelty interaction, with a strong emphasis on productivity, scale-ability and cost reductions. In the case of chat-bots, there has been a immense requirement to simulate human-like characteristics and behaviors during human-machine interactions[8]. Per Kusal et al. [1] these chat-bots also improve customer engagement by offering friendliness, comforters, flexibility, and efficient assistance. As such chat-bots should provide customers with more engaging responses, directly addressing their issues or questions. The goal of deploying ED to these applications is for users perceive chat-bots as companions rather than simple assistants, which in turn helps the overall process of getting to a positive result. Per Adikari et al. the majority of user requests are emotional rather

than informative; therefore the need for chat-bots to gain the capacity to respond emotionally to customers via machine learning and sentiment analysis evolution[1] is very important and yields for many applications that use ED a way to improve interactions with machines.

I usually know almost exactly how I feel. The problem is, I just can't tell anyone.

– Meg Cabot

Due to the above mentioned wide scope of uses for ED this field of research and the work to advance it provides significance and importance in enabling machines to comprehend and respond appropriately to human interactions. Our research in turn contributes to the advancement of artificial intelligence, natural language processing (NLP) and in many cases the utilization of text-to-speech applications most all of us in today's society use and rely on [13] to go about our daily lives.

Lastly, in the paper by Chen et al.[2] based on emotion detection for online learning it states, interestingly, that with emotion recognition research, we need to focus on accuracy and real-time performance in order to apply ED based on physiological signals to solve practical problems; the key part of their claim is that in order for ED to be practical, real-time methods need to be used and deployed for maximum results.

1.3 Challenges: Lack of Labeled Datasets and Language Fragmentation

Emotion Detection is a fast growing field[17, 18], however unlike Sentiment Analysis (SA) the availability of large datasets for training purposes of ML models is much smaller [17, 13]. The primary reason of the lack of data stems from the fact that emotion detection data requires primarily supervised learning data. In turn requires time and effort to construct, catalog, and procure; this all is mostly created and labeled by humans. To compound on the issue of the lack of labeled data; the many datasets that are available are in many cases in multiple languages - not all are in English since emotions that are linked to text are contextual in nature. for this research a significant amount of time took place to find the German labeled data, which eventually was found online by google searching.

1.4 Motivation for the research project focusing on extending ED datasets through translation and evaluating the impact on prediction rates

This paper is significant because an entire industry of automated emotion reading (Text, Image, Video, and Sound) technologies is quickly emerging [17, 18]. The market for emotion recognition and detection software is forecast to reach at least \$3.8 billion by 2025 [17, 18]. And since ED is already being incorporated into products for purposes such as marketing, robotics, driver safety, customer service, news and stance analysis, and a multiple of others, it is fitting to work on research to solve and / or improve issues in regards to prediction rates due to lack of data and language fragmentation.

With the above mentioned issues regarding the quantity (lack of) and language fragmentation of the ED datasets this research was motivated by finding a way to combine different language datasets into a single set for training processes to improve the predictability of ED. The aim of the research is that by use of translation that the predictability of ED can be improved by extending an English

dataset with translations from German and also process look-ups in real-time language conversion and processing.

1.5 Objectives & Scope of the Research

The primary objective of this Qualifying Exam research project is to address three (3) research questions, each aimed at improving the accuracy of predictive ED models in the context of English and German language datasets.

- The first hypothesis is that by introducing English data translated into German and extending an original German dataset, will the added text lead to an enhancement in its predictive capabilities. (Section 4.2)
- Similar to the first, can by translating German data to English and extending an original English dataset increase the predictability of English ED model? (Section 4.2)
- The third research question shifts the focus to real-time translation and its impact on prediction. Can by translating in real-time an input to multiple languages improve the predictability based on the combined output of two models that were trained in English and German to better the prediction results. (Section 4.3)

In summary, this research project centers around investigating innovative ways to enhance the predictability of Emotion Detection models in both English and German. With these three (3) objectives from above our methodology will be to procure, translate, train, and evaluate benefits of extending datasets by translation to improve emotion detection.

2 Literature Review

To ensure comprehensive coverage of the latest developments and research in emotion detection and analysis for this research paper, consideration and review was only given to incorporating research papers and online news articles that were published after the year 2015, thereby providing an up-to-date perspective on the subject matter at hand.

We believe by implementing the 2015 boundary, our methodology and results aim to provide a more up-to-date outlook on the subject matter at hand and what areas the emotion detection field is moving in with respect to machine learning research, applications and processes.

2.1 Emotion Detection Importance and Diverse Populations

Emotion Detection (ED) holds significant importance[15] in various domains, including psychology, social sciences, and human-computer interaction. By use of ML models[3] the analysis of human emotions at scale, providing valuable insights into individual and collective emotional states both in real-time but also as a type barometer for measuring sentiments from the past versus the current time. In Chowanda et al. paper[3] they believe that "Emotions hold a paramount role in the conversation, as it expresses context to the conversation.", this means that emotions are a part of a conversation and with that are needed to ensure valid analysis of a conversation.

Furthermore Kapoor et al. [7] states that, emotions can differ across age groups, genders, cultures, and languages. Including data from diverse populations helps in developing inclusive and culturally sensitive ED models. It ensures that the models are not biased towards specific groups and can accurately detect emotions in a wide range of individuals.

2.2 Lack of Labeled Datasets and Fragmentation caused by Different Languages

The lack of diverse and large-scale data hinders the development and training of accurate ED models, limiting their effectiveness and general ability across different contexts and populations. In recent research, efforts have been made to address these limitations by exploring new techniques for emotion detection.

For instance, a study by Kapoor[7] et al. proposes analyzing the entire spectrum of the language source to predict emotional changes. This provided some help, but quickly established itself as time consuming task and need of expertise in the subject matters that could not outweigh the results. Overcoming the scarcity of labeled datasets and embracing innovative approaches like the above mentioned study by Kapoor[7] et al. and their analysis can contribute to the advancement of ED research. Such advancements hold the potential to enhance the accuracy and applicability of emotion detection models, enabling a deeper understanding of human emotions and more effective responses in various domains, although the cost of such might be prohibitive at this time.

In addition, the paper by Mascarell[10] et al. states that unlike images language operate very differently, therefore the lack of labeled datasets poses a significant challenge in text-based Emotion Detection (ED) analysis as it limits the availability of reliable training data for ML models. This scarcity hampers the model's ability to learn and generalize emotions effectively.

And lastly, a paper by Kusal et al. further stipulates [9] that the fragmentation caused by different languages further exacerbates the issue, as it reduces the size and diversity of data available for training, resulting in limited cross-lingual generalization and potentially biased models.

Overcoming these challenges, lack of data and language fragmentation, is crucial for advancing emotion detection and analysis research for improving the accuracy, speed, and applicability of ML models across various languages and cultures.

3 Methodology

3.1 Data Procurement and Parsing of ED datasets in English and German

The data procurement was relatively straight forward and once found by using multiple Google search terms for the Emotion Detection in English and German text languages. Some of the main German data was obtained from the dataset built by ETH’s Emotion and Stance Detection for German Text [10] which also hosts a good website with their findings². The English dataset was downloaded from Kaggle³ based on Tweets collected in 2021. The English dataset contains over 38,000 tweets and their corresponding emotion’s labeled. Unfortunately the German dataset only contained just over 2,500 sentences and their respective emotions associated with it. Unfortunately this imbalance (see Table 1) of the two dataset sizes will had to be corrected and is explained in detail in the subsequent sections.

File Details		
Name	Row Count	Type
English	38,000	CSV
German	2,500	JSON

Table 1: File details of English & German data.

An important part of the process is to make sure we match / link the English emotions to those of the German language emotions. Since the two languages are dissimilar we opted to match exact emotions to each other that can be seen in Table 2 below. The linking yielded our eight (8) emotions we previously discussed in Sections 1.1. Details on how we formatted the the two (English and German) datasets to each other can be viewed in the Appendix A.2 and A.3.

The processing of two ED datasets to be synchronized or linked to the emotion is important. The first will be in English and the second in German. Each dataset will be translated into the other’s language for extension purposes.

We decided to build the data to support that each row of each dataset will hold the English and German sentence. As an example Figure 2 depicts the original English dataset will be extended by the translated German (German \Rightarrow English) dataset. By this simple process the English dataset got larger for training purposes.

The reason for selecting German in this research project was based on the author⁴ being fluent in English and German and hence being able to easily traverse the two languages while working on the code for dataset translations and formatting. It was much easier to create the emotion cross reference Table 2 and also check the translation results due to the dual language benefit.

Once the two datasets have been translated, we now extend the original language dataset with the translated one. By this approach we are in essence extending the original datasets to create a larger one with the foreign language data. With both extended datasets we can now train our ML models

²<https://mtc.ethz.ch/research/natural-language-processing/emotion-stance.html>

³<https://www.kaggle.com/datasets/pashupatigupta/emotion-detection-from-text>

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Emotion Datasets Labels				
English		German		Used
Name	Count	Name	Count	
Boredom	179	—	—	NO
Love	3842	Vertrauen	316	YES
Relief	1526	—	—	NO
Fun	1776	—	—	NO
Hate	1323	Ekel	29	YES
Neutral	8638	Unklar	314	YES
Anger	110	Ärger	226	YES
Happiness	5209	Freude	140	YES
Surprise	2187	Überraschung	369	YES
Sadness	5165	Traurigkeit	184	YES
Worry	8459	Angst	154	YES
Enthusiasm	759	Antizipation	774	YES
Empty	827	—	—	NO

Table 2: Dataset of English & German and their respective label counts.

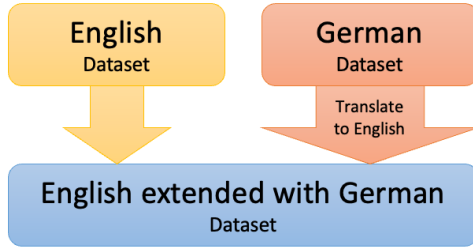


Figure 2: Example of English dataset extension by translating from German.

for English and German.

3.2 Translation Application for Converting English to German and Vice Versa

Translation of the emotion datasets was performed with Google Translator based on the Medium article[12] in which the author describes options for simple API translations. Google Cloud Translation was used mainly due to its free nature and ease of use for this project. There are however many other text based API translation services that could have been used and might yield in some circumstance even better results.

As an example the following is a brief introduction to Google Translator’s API with the code snippet below depicting the ease of use to translate text via an API.

```

1 # Using Deep Translator to leverage Google Translate
2 # Link: https://cloud.google.com/translate/docs/reference/libraries/v2/python
3 from deep_translator import GoogleTranslator
4
5 sentence = 'Chocolate milk is so much better through a straw.'
6
7 translated = GoogleTranslator(source='auto', target='de').translate(sentence)
8 print(translated) # Schokoladenmilch schmeckt durch einen Strohhalm viel besser.
9
10 translated_back = GoogleTranslator(source='auto', target='en').translate(translated)
11 print(translated_back) # Chocolate milk tastes much better through a straw.

```

Source Code 1: Google Translate Example Code

Based on the above translation example the CSV⁵ (English) and JSON⁶ (German) datasets were individually loaded, parsed, and translated to their respective counter-part languages. Details of the application can be found in the Appendix A.2 for English and Appendix A.3 for the German processing. We decided to only use 1,500 rows from each language. This decision was made since the German (DE⁷) dataset was not much larger than that once filtering and processing was completed. This meant that the English (EN⁸) dataset was randomly paired down to 1,500 to match that of the German.

Each translated file now contains four (4) columns that are labeled in Tables 3 and 4 with the exact same column naming.

File: pd_de_translated.csv			
sentence_de	emotion_de	sentence_en	emotion_en
Original Sentence (feature)	Original Emotion (label)	Sentence Translated to English	Emotion set by Cross-Reference from German

Table 3: German CSV file structure after translation to English

File: pd_en_translated.csv			
sentence_en	emotion_en	sentence_de	emotion_de
Original Sentence (feature)	Original Emotion (label)	Sentence Translated to German	Emotion set by Cross-Reference from English

Table 4: English CSV File structure after translation to German

⁵CSV = Comma Separated Values

⁶JSON = JavaScript Object Notation

⁷DE = German

⁸EN = English

3.3 Training Multiple ML models with PySpark

After the completion of translating and processing the English and German datasets we come to training our models. Using the datasets from Tables 3, 4, and 5 that list an approximate $\sim 1,275$ and $\sim 2,775$ features for training.

It is important to note that in order to accurately test and compare the original and the extended datasets to each other we made sure that the test data was the same on each case. To do this we randomly extracted 15% of the original datasets (English and German) and saved it as a test dataset prior to extending the original with the translated sentence data.

```
1 # Split the English and German Dataframes for Training and Testing
2 # We are using a 15/85 Split
3 df_en_train, df_en_test = df_en.randomSplit([0.85, 0.15], seed=2023)
4 df_de_train, df_de_test = df_de.randomSplit([0.85, 0.15], seed=2023)
5
6 # Create the Extended Dataframe with Translated Data
7 # It is important to add the translated to the training data and not all of it
8 # Using *df_en_train.columns ensure that the columns are matched with the union
9 df_en_train_extended = df_en_train.union(df_de.select(*df_en_train.columns))
10 df_de_train_extended = df_de_train.union(df_en.select(*df_de_train.columns))
```

Source Code 2: Linking the English and German Emotions to the same label

In Chowanda et al. paper[3] on Text-based Emotion Techniques multiple algorithms were proposed, our research focused on just three (3) out of the six from the paper since the others had lower prediction rates based on the papers conclusions. The algorithms tested in this research project ranged from the traditional machine learning to deep learning techniques, they are:

- **Naïve Bayes:** Per Pujan’s paper[21] on the Naïve Bayes model, it classifies and/or assigns the most likely class to a given example based on its feature vector, simplifying the task greatly by assuming that the features are independent given a class.
- **Generalised Linear Model (GLM):** Per Mueller’s paper on GLM[11] the Generalized linear models extend the concept of the well understood linear regression model.
- **Random Forest Classifier:** Per Schonlau’s paper[16] on the Random Forest Classifier, they state that random decision forests easily adapt to non-linearity found in the data and therefore tend to predict better than linear regression. More specifically, ensemble learning algorithms like random forests are well suited for medium to large datasets.

Each of these algorithms used and their results are listed in the Results and Analysis Section 4 below.

The results of the testing resulted in some interesting parts that can be viewed in Table 6. We grouped the label by count from the test data (both English and German) and compared the predicted result counts to those. It became very clear that there was a strong bias on the GLM (Linear Regression) model that essentially proposed that all sentences evaluated to the same output both in English and German.

ML Models			
Model	Data	Rows for Training (85%)	Rows for Testing (15%)
A	English Original	1,275	225
B	English Extended By German	2,775	225 same as Model "A"
C	German Original	1,275	225
D	German Extended By English	2,775	225 same as Model "C"

Table 5: ML Models and their respective Train and Test Rows

3.4 Creating an API for Translation and Parallel Processing

In order for a user to access and get prediction results from all three (Random Forest, Naives Bayes, and Linear Regression) ML models trained in both English and German in real-time we crated a Jupyter Notebook that starts an Apache PySpark⁹ session that is accessed via the local server listen on <https://127.0.0.1:8080>. The details of the RESTful the server can be found in Appendix B.2.

The server listens for GET requests and evaluates a querystring either called `sentence_en` or `sentence_de` if an English sentence is sent then the server translates to German and if a German is sent then it translates to English. Each sentence is then tokenized, formatted, and processed on the previously trained ML models in both languages.

Once all the the ML model predictions have completed, we then lookup the emotion associated with the individually predicted labels and build a response `JSON` object to pass back the calling application. The `JSON` object (Source Code: 3) contains the original sentence and translated, plus each emotions predicted label by the six previously trained models. In addition the main data, and `metadata` object is created that holds the PySpark version, start, and end times, including the processing time in seconds.

⁹PySpark: <https://spark.apache.org/docs/latest/api/python/index.html>

```

1 {
2   "metadata": {
3     "datetime": {
4       "elapsed": 1.651038,
5       "end": "Mon, 14 Aug 2023 12:10:35 GMT",
6       "start": "Mon, 14 Aug 2023 12:10:33 GMT"
7     },
8     "spark": "3.3.2"
9   },
10  "predictions": {
11    "de_lr": "enthusiasm",
12    "de_nb": "relief",
13    "de_rfc": "enthusiasm",
14    "en_lr": "neutral",
15    "en_nb": "love",
16    "en_rfc": "happiness"
17  },
18  "sentence": {
19    "english": "What a wonderful world this is!",
20    "german": "Was für eine wundervolle Welt das ist!"
21  }
22 }

```

Source Code 3: JSON output from API

3.5 Evaluation Metrics and Methodologies for Measuring the Performance

The evaluation of ML models trained on the English, German and their respective extension datasets is a critical step in assessing their performance and reliability. We chose to use the MulticlassClassificationEvaluator¹⁰ because is a well known tool in the field of natural language processing (NLP) research, specifically in multi-class classification tasks such as emotion detection that has multiple labels associated with it; in our case eight (8) see Table 2 on Page 10. Generally this evaluator is used to evaluate the performance of machine learning (ML) models, using transformer-based architectures like BERT, RoBERTa, or DistilBERT[14], with DistilBERT[14] being the one we used in this research project.

The MulticlassClassificationEvaluator provides the essential evaluation metrics, including accuracy, Precision (eq: 2), Recall (eq: 4), and F1 Score (eq: 6) for ED classifications. These metrics provide valuable insights into a model's ability to correctly classify emotions across multiple classes and languages. Our research project is no different and the following measurements were used for our analysis:

- **Accuracy:** Accuracy measures the overall correctness of the emotion predictions made by the model. It is calculated as the ratio of correctly classified instances to the total number of instances in the dataset.

¹⁰URL: <https://spark.apache.org/docs/latest/api/python/reference/api/pyspark.ml.evaluation.MulticlassClassificationEvaluator.html>

¹¹In the NB a result that cannot be matched is a zero label

ML Models Test versus Test Result Counts					
English					
ID	Label	Test Data	NB Res	GLM Res	RFC Res
0	boredom	0	25 ¹¹	0	0
1	love	26	8	3	11
2	Relief	0	33	0	0
3	Fun	0	5	0	0
4	hate	9	31	0	0
5	neutral	50	21	152	101
6	anger	0	36	0	0
7	happiness	39	44	5	17
8	surprise	10	9	0	1
9	sadness	29	0	2	19
10	worry	46	0	50	63
11	enthusiasm	3	0	0	0
German					
ID	Label	Test Data	NB Res	GLM Res	RFC Res
0	boredom	0	34	0	0
1	love	25	5	0	13
2	Relief	0	28	0	0
3	Fun	0	16	0	0
4	hate	5	16	0	2
5	neutral	30	24	0	5
6	anger	23	20	1	7
7	happiness	10	20	0	5
8	surprise	24	47	0	11
9	sadness	12	0	0	2
10	worry	9	0	209	4
11	enthusiasm	72	0	0	161

Table 6: Prediction Results Count compared to Test Data Label Counts

- **F1 Score:** Precision represents the proportion of correctly predicted emotions among all instances predicted as a specific emotion with respect to the labels. Recall measures the proportion of correctly predicted emotions among all instances that truly belong to a specific emotion. With these two the F1 Score ($F1_{score} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$) combines precision and recall into a single metric, providing a balanced evaluation.

While evaluating the models we focused on the Accuracy and the F1 Score to illustrate the prediction results of the original versus extended datasets, and also compared the different algorithms to each other. As an added example simply using the accuracy to evaluate a model can be miss-leading and therefore in our case using the F1 Score, that is directly correlated to the Precision (eq: 2 and Recall (eq: 4) is immensely important to understanding the ones models and finding the best of for

the task of Emotion Detection using Original and Extended datasets.

3.6 Using an API to Translate in Real-Time for Dual Prediction

The last stage of this research project was devoted to testing the API by use of a simple webpage. In order to accurately test and get real-world results and a sense on the real-time processing of a Emotion Detection a simple webpage was build to give a user the sense of the conclusion of the project. In Figure 3 a brief screenshot of some testing can be seen.

The screenshot displays a web interface titled "ML Prediction API Demo" with the subtitle "Qualifying Exam - August, 2023". It features two input fields: "English" containing "I am so happy about this news!" and "German" which is empty. A blue "Predict" button is to the right. Below the inputs are two green boxes showing predictions: "HAPPINESS" for the English text and "FUN" for the German text. Underneath these are corresponding German translations in grey boxes: "I am so happy about this news!" and "Ich freue mich sehr über diese Neuigkeiten!". At the bottom, the "API Response:" is shown as a JSON object in a grey box.

```
{
  "metadata": {
    "datetime": {
      "elapsedInSeconds": 1.642335,
      "end": "Mon, 14 Aug 2023 15:24:58 GMT",
      "start": "Mon, 14 Aug 2023 15:24:56 GMT"
    },
    "spark": "3.3.2"
  },
  "predictions": {
    "de_lr": "enthusiasm",
    "de_nb": "fun",
    "de_rfc": "enthusiasm",
    "en_lr": "neutral",
    "en_nb": "relief",
    "en_rfc": "happiness"
  },
  "sentence": {
    "english": "I am so happy about this news!",
    "german": "Ich freue mich sehr über diese Neuigkeiten!"
  }
}
```

Figure 3: Demo API Webpage

In the screenshot (Figure: 3) example a sentence was entered in the English text-box and the "Predict" button pressed. The API took about ~1.6seconds to translate the English to German and then process both sentences on the pre-trained ML models, build the JSON object and return it to the application.

3.7 Written & Oral Presentation of Research Finding

In conclusion of the project a research paper and oral presentation is required to pass the MTSU Computation Data Science PhD Qualifying Exam. The listing of all the datasets used, code

for the application, and details of the research project process in this research paper is openly available and hosted on a GitHub repository, allowing for easy access, reproducible, and collaborative engagement with the research findings. The repository is open and available under: <https://github.com/richardhoehn/mtsu.coms.qualifying-exam>[5]. In addition of all the code being listed in a public repository the paper was comprised and build using L^AT_EX¹².

Using L^AT_EX for this paper provides numerous benefits, some of which are portability, source control (due to plain-text nature), bibliography management, and last but not least the ability to write clean mathematical equations.

¹²L^AT_EX UR: <https://www.latex-project.org/>

4 Results and Analysis

This section lists the prediction rates of training and testing of the original and extended datasets both in English and German. Overall results seem to indicate that there was no measurable benefit and even negative outcomes from adding the extended data for Emotion Detection. In the subsections details on the results are listed by the common standards of using the below equations 1, 2, 4, and 6 for Accuracy, Precision, Recall, and the F1 Score. It should be noted that ED is a multi-class classification problem, which means that the machine learning process assigns the predictions from the sentence data to one of several predefined emotion categories (see Table 2).

4.1 Prediction Results of Original & Extended Datasets

Overall the prediction results from the trained models is disappointing. Using the Random Forrest Classifier described in Section 3.5 provided the best prediction results based on a combination of the Accuracy and the F1 Score. It should be noted although the accuracy may be slightly better on the GLM models for both English and German, if one reviews the F1 Score, the RFC model performs better.

Oddly, the prediction results with the extended data where lower than using the original (non-extended) data for training. In the Analysis and Conclusions section 4.2 details on why this may be the case are discussed in detail.

4.1.1 Formulas and Equations used in Analysis

The accuracy (eq: 1) of any machine learning model is a clear and easily comprehend-able way to understand the performance of a model. However, it is important to consider the context and potential trade-offs with other metrics, as high accuracy alone might not adequately capture the full picture of a model's performance. This can be especially true for multi-class classification models such as the ED analysis that we are working on.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

The Precision (eq: 2) focuses in detail on the accuracy of positive predictions (TP)¹³ made by the model. According to Google Cloud's definition, precision answers the question: What proportion of positive predictions were actually correct?

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Since our project is a multi-class classification project we will need to utilize Micro Averaging for the Precision. With this in mind, we extend our simple equation 2 for precision to incorporate micro averaging as defined in equation 3.

¹³Positive Predictions = TP (True Positive)

$$Precision_{MicroAvg} = \frac{(TP_1 + TP_2 + \dots + TP_n)}{(TP_1 + TP_2 + \dots + TP_n + FP_1 + FP_2 + \dots + FP_n)} \quad (3)$$

The Recall (eq: 4) focuses on the in detail on the accuracy of positive predictions¹⁴ made by the model. Per Google Cloud’s definition: The recall attempts to answer: What proportion of actual positives.

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

Since our project is a multi-class classification project we will need to actually use Micro Averaging for the Recall in a similar fashion to how we used it on Precision. With this in mind we extend our simple equation 4 of recall to incorporate micro averaging as defined in equation 5.

$$Recall_{MicroAvg} = \frac{(TP_1 + TP_2 + \dots + TP_n)}{(TP_1 + TP_2 + \dots + TP_n + FP_1 + FP_2 + \dots + FP_n)} \quad (5)$$

The F1 Score (eq: 6) in our project is important to assess the balance between precision and recall. In addition, the F1 Score holds significance in multi-class classification scenarios where there are more than two classes.

$$F1_{Score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (6)$$

Lastly, we employed micro averaging for the Recall, Precision, and F1 Score due to the fact that it assigns equal weight to each label (Emotion, as seen in Table 2), regardless of the class label and the number of labels taken into account. This approach ensures that the evaluation metrics give uniform importance to all labels, making it particularly suitable for scenarios where class imbalances exist or where an fair assessment of model performance across all emotion classes is required.

4.1.2 English Dataset Results

The Table 7 lists the results of all three ML models, their accuracy and F1 Score based on the English original and extended datasets. The improvements from the original and extended datasets are listed in the last column. In all cases the improvement to using the extended datasets was negative.

4.1.3 German Dataset Results

The Table 8 lists the results of all three ML models, their accuracy and F1 Score based on the German original and translated from English to German extended datasets. The improvements from the original and extended datasets are listed in the last column. Interestingly the Random

¹⁴Negative Predictions = FN (False Negative)

Results of English Dataset					
	Original Dataset		Extended Dataset		
	Accuracy	F1 Score	Accuracy	F1 Score	Improvement
Random Forrest	29.72%	25.83%	21.23%	19.43%	-28.56%
Naïve Bayes	5.66%	6.92%	3.77%	4.14%	-33.39%
GLM (lr)	32.08%	23.68%	25.47%	16.19%	-19.95%

Table 7: Model Testing Results on English Dataset

Forrest Classifier was the only negative improvement whereas the GLM and Naive Bayes models had improvements. However it should be noted that the prediction rates are so low in the GLM and Naive Bayes that they should not really be considered improvements.

Results of German Dataset					
	Original Dataset		Extended Dataset		
	Accuracy	F1 Score	Accuracy	F1 Score	Improvement
Random Forrest	28.10%	16.84%	25.71%	18.56%	-8.50%
Naïve Bayes	4.29%	4.31%	6.67%	4.21%	+55.48%
GLM (lr)	34.29%	17.57%	24.76%	18.27%	-27.79%

Table 8: Model Testing Results on German Dataset

The improvements on the accuracy are based on Equation (7) listed below. It is a simple and straightforward way of comparing the Accuracy from the original trained dataset to the extended trained dataset for purposes of comparing the potential benefits of extending the training datasets by translation.

$$Improvement(\%) = \frac{(Accuracy_{Ext}(\%) - Accuracy_{Org}(\%))}{Accuracy_{Org}(\%)} \quad (7)$$

It should be noted that although the improvement values are fairly large negatives those come from the fact that the accuracy is small and in most all cases the accuracy is around the 25 - 30% values and a change of just a few percent can have a significant impact on the improvement values.

4.2 Analysis of the impact of Extending Datasets by Translation

While extending datasets for machine learning training can often improve[15] model performance, it's important to recognize that this approach has its limitations, especially in ML models that can reach a limit on training data. In our case, relying on translation services for dataset expansion might not consistently yield better results when extending the data from translated text. These services, in our case using Google Translate¹⁵ can introduce errors or inaccuracies in translations especially in the context of emotions of a particular text, leading to noisy or incorrect training data. Consequently, the models may learn from erroneous information, which did negatively impact our models performance on the ED tasks.

¹⁵Google Cloud Translate URL: <https://cloud.google.com/translate>

Specifically in our case of extending the original English and German datasets with translated data seems to indicate that the sentences and structure are not the same and therefore the prediction rates went down as the models got more diluted.

4.3 Impact Using API for Real-Time Translation

With the help of the webpage (Figure 3 on 16) a sense of the inaccuracy was also presented. Each round trip to the API took an between 1.4 and 1.6seconds. The prediction results mirrored those of Tables 7 and 8 which in turn made the usefulness of the translation not practical as can be seen in Table 9 below.

Webpage API Test					
	English		German		
Test	Emotion	Sentence	Emotion	Sentence	Time
A	Worry	This is bad idea and we need to stop right now	Anger	Dies ist eine schlechte Idee und wir müssen jetzt aufhören	1.49s
B	Happiness	What a wonderful world this is!	Relief	Was fur eine wundervolle Welt das ist!	1.65s
C	Happiness	I am so happy about this news!	Fun	Ich freue mich sehr uber diese Nauigkeiten!	1.64s
D	Sadness	Gosh I hate doing this today.	Relief	Meine Güte, ich hasse es heute.	2.56s

Table 9: API Webpage Test Results

4.4 Findings and Implications for Improving Emotion Detection

Based on the improvement results in Sections 4.1.2 and 4.1.3 it seems that using translation to extend both the English and German datasets resulted in a negative outcomes. The best outcomes were using a simple Linear Regression model on the English and German, however based on the F1 Score (Eq: 6) of the Random Forest Classifier it seems to perform the best on both English and German. This is because the false positive amount of one score on the accuracy is not taken into account and can easily skew the results when using a multi-class classification model.

Considering the outcomes of data extension via translation, our approach of utilizing real-time translation for multi-language models through the creation of an API and translating text in real-time for both German and English appears to be unsatisfactory in terms of achieving any substantial improvement as well.

With both these findings, we believe that the data of only using $\sim 1,500$ (original dataset) and $\sim 2,700$ (extended dataset) to train models is insufficient[20] when using a multi-class classification problem. By inference, if we have only 1,500 and divide (eq: 8) those by our eight (Table: 2) classes we simply do not have enough data to truly train the ML on the classes.

$$\begin{aligned} \frac{Features}{Labels} = \frac{Sentences}{Classes} = \frac{1,500}{8} = 185 \\ or = \frac{2,700}{8} = 337 \end{aligned} \tag{8}$$

Taking into account the insufficiency of data, the implication of a lack of classified data can lead to several significant issues for our ML models. Firstly, there’s an absence of context for the models to operate effectively and grasp the intricate nuances of both the English and German languages. Secondly, in cases where class data is lacking, the models tend to memorize existing sentences and words, rather than learning the underlying patterns of the language. Both of these issues are connected to a phenomenon called overfitting[20], which is prevalent in many regression problems.

Options for improvement range from the straightforward approach of acquiring more data to the more nuanced strategy of leveraging existing labeled sentences and employing machines to generate derivatives. This would facilitate the creation of more intricate patterns for the machines to learn from.

4.5 Conclusion and Future Work

It’s crucial to ensure the quality and accuracy of extended data, especially when language translation is involved, to prevent introducing more noise than meaningful information into the training process. The implications of the lack of data in ED analysis presented itself in this research that sought to try and overcome these issues. Although the research did not yield any significant improvements through translating the German to English as a means of extending the English dataset, it ultimately worsened the prediction results. We believe one of the main culprits is that the data for learning based on eight classes was insufficient. As can be seen in Equation 8 from Section 4.4, the models seemingly resorted to memorizing the sentence rather than learning the intricacies of the labeled classes. This inference arises that certain labels exhibited better F1 Score performance, primarily due to their greater availability in the training data.

Two areas of prospective research emerge: firstly, conducting further tests involving the translation of different models using diverse translation services. While Google Cloud’s translation service sufficed for this research, superior paid subscription-based translation services are available. With the help of more data and better translation more concrete answers to improving predictions may be achieved. Secondly, another avenue to overcome the lack of data involves employing AI to generate sentences that are similar yet distinct from the original. This could be achieved by providing a sentence and its associated labeled class to the AI for data creation. This approach aims to produce additional sentences imbued with similar emotional attributes, potentially expanding the labeled dataset.

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A Appendix – Dataset Details

The following details in this appendix are for clarification purposes. All examples in this appendix are created via Panda and PySpark using data frames.

A.1 Translation Setup

All example code was created using Jupyter Notebooks.

```
1 import pandas as pd
2
3 # This was predetermined by review of the emotion from English to German
4 emotion_key = {
5     "boredom": "---",
6     "love": "Vertrauen",
7     "relief": "---",
8     "fun": "---",
9     "hate": "Ekel",
10    "neutral": "Unklar",
11    "anger": "Ärger",
12    "happiness": "Freude",
13    "surprise": "Überraschung",
14    "sadness": "Traurigkeit",
15    "worry": "Angst",
16    "enthusiasm": "Antizipation",
17    "empty ": "---",
18    "---": "Keine"
19 }
20
21 # Create a DataFrame from the emotion_key dictionary
22 df_emotions = pd.DataFrame(emotion_key.items(), columns=['emotion_en', 'emotion_de'])
23
24 # *****
25 # *** Translation ***
26 # *****
27 from googletrans import Translator
28 import time
29
30 # This google API take a Sentence and converts to German
31 def translate(sentence, dest_lang):
32     try:
33         translator = Translator()
34         translator.raise_Exception = True
35         translation = translator.translate(sentence, dest=dest_lang)
36         time.sleep(0.5) # Add a 1-second delay
37         return translation.text
38     except Exception as e:
39         print(f"Translation Error: {e}")
40         return None
```

A.2 Details on English Dataset Parsing and Formatting

The English dataset is based on tweets¹⁶ that are saved as a csv¹⁷ file. The following code was used to filter and process the file for use in this project.

```
1 # *****
2 # *** English Data Preparations ***
3 # *****
4 import pandas as pd
5 from tqdm import tqdm
6
7 # Load English CSV File into a Dataframe
8 df_en = pd.read_csv("data/english.csv")
9 print(f'Count (row): {len(df_en)}')
10
11 # Print Columns
12 print(f'English Source Columns: {df_en.columns}\n')
13
14 # Filter only labels that we matched with the German counter part JSON File
15 filter_values = ["love", "hate", "neutral", "anger", "happiness", "surprise", "sadness", "worry", "enth
16 df_en = df_en[df_en["sentiment"].isin(filter_values)]
17
18 # Find Empty Sentence Values
19 df_en = df_en[df_en["content"].notnull() & (df_en["content"].str.strip() != '')]
20
21 # Remove unnecessary column
22 df_en = df_en.drop("tweet_id", axis=1)
23
24 # Rename Columns
25 df_en = df_en.rename(columns = {'sentiment': 'emotion_en', 'content': 'sentence_en'})
26
27 # Merge German Emotions onto English
28 df_en = pd.merge(df_en, df_emotions, on='emotion_en', how='left')
29 df_en["sentence_de"] = "" # Add German Sentence Column
30 df_en = df_en.sample(n=1500, random_state=2023) # Randomly select 1500 rows
31
32 df_en.to_csv('./data/pd_en.csv', index=False)
33
34 # Iterate over the rows with tqdm to show the progress
35 for index, row in tqdm(df_en.iterrows(), total=df_en.shape[0]):
36     # Call Translation
37     sentence = translate(row["sentence_en"], 'de')
38     # Save Sentence on Column
39     df_en.at[index, 'sentence_de'] = sentence
40
41 df_en.to_csv('./data/pd_en_translated.csv', index=False)
```

¹⁶Tweets from Twitter

¹⁷csv = Comma Separated Values

A.3 Details on German Dataset Parsing and Formatting

The German dataset was downloaded from the ETH's¹⁸ servers via "link" as a JSON file. Since the file was JSON we will need to filter and explode the file based on the emotions that are attached to it.

```
1 # *****
2 # *** German Data Preparations ***
3 # *****
4 import pandas as pd
5 from tqdm import tqdm
6
7 # Load German JSON File into a DataFrame
8 df_de = pd.read_json("data/german.json", lines=True)
9 print(f'Count (row): {len(df_de)}')
10
11 # Print Columns
12 print(f'German Source Columns: {df_de.columns}\n')
13
14 # Explode the "article_emotion" column to distinct rows
15 df_de = df_de.explode('article_emotion')
16
17 # Filter only labels that we matched with the German counter part JSON File
18 filter_values = ["Vertrauen", "Ekel", "Unklar", "Ärger", "Freude", "Überraschung", "Traurigkeit", "Angst"]
19 df_de = df_de[df_de["article_emotion"].isin(filter_values)]
20
21 # Find Empty Sentence Values
22 df_de = df_de[df_de["title"].notnull() & (df_de["title"].str.strip() != '')]
23
24 # Remove unnecessary columns
25 df_de = df_de.drop("article_id", axis=1)
26 df_de = df_de.drop("article_stance", axis=1)
27 df_de = df_de.drop("paragraphs", axis=1)
28 df_de = df_de.drop("source", axis=1)
29 df_de = df_de.drop("snippet", axis=1)
30
31 # Rename Columns
32 df_de = df_de.rename(columns={'title': 'sentence_de'})
33 df_de = df_de.rename(columns={'article_emotion': 'emotion_de'})
34
35 # Merge English Emotions onto German
36 df_de = pd.merge(df_de, df_emotions, on='emotion_de', how='left')
37 df_de["sentence_en"] = "" # Add English Sentence Column
38 df_de = df_de.sample(n=1500, random_state=2023) # Randomly select 1500 rows
39
40 df_de.to_csv('./data/pd_de.csv', index=False)
41
42 # Iterate over the rows with tqdm to show the progress
43 for index, row in tqdm(df_de.iterrows(), total=df_de.shape[0]):
```

¹⁸ETH (German: Eidgenössische Technische Hochschule) or Swiss Federal Institute of Technology

```
44     # Call Translation
45     sentence = translate(row["sentence_de"], 'en')
46     # Save Sentence on Column
47     df_de.at[index, 'sentence_en'] = sentence
48
49 df_de.to_csv('./data/pd_de_translated.csv', index=False)
```

B Appendix – Application & Code Details

In this appendix we aim to supply details to the code and application blocks of this project. It should be noted that some of the code has been edited to fit on these pages and might not represent verbatim the code in the GIT repository.

All code was developed and test using a MacBook PRO running **Ventura 13.4.1**. Since PySpark was developed for cluster processing it may seem counter intuitive to build PySpark code for a Mac; however the intent is that some of this research can be further used on clusters in the future.

B.1 PySpark Session Setup

```
1 # Setup Spark Session
2 from pyspark.sql import SparkSession
3
4 # Get Imports Needed
5 from pyspark.sql.functions import col, udf, regexp_replace, lower
6 from pyspark.sql import functions as F
7
8 # Get Datatypes needed for DataFrame manipulation
9 from pyspark.sql.types import IntegerType, StringType, ArrayType
10
11 # Other Imports
12 import re # Import the "re" module for regular expressions
13
14 # Setup Spark Session
15 sc = SparkSession \
16     .builder \
17     .master("local[*]") \
18     .appName("Qualyfing-Exam") \
19     .getOrCreate()
20
21 # Print Spark Version being run
22 print("Spark V: ", sc.version)
```

B.2 RESTful API Server

The RESTful¹⁹ API Server will be a simple Python Flask server listening on port 8080 on the local machine.

Flask is a lightweight and simple to use web framework in Python, allowing developers to create web applications and APIs. Due to its simplicity and components design, Flask allowed us to rapidly build and interactive web service for demonstration purposes on this project.

```
1 # Setup Spark Session
2 from pyspark.sql import SparkSession
3
4 # Import API Modules
5 from flask import Flask, request, jsonify
6 from flask_cors import CORS
7 import datetime
8
9 # Import Translator
10 from googletrans import Translator
11
12 # Import Tokenizer and Pipeline Tools
13 from transformers import DistilBertTokenizer
14 from pyspark.ml.pipeline import PipelineModel
15
16 # Setup Spark Session
17 sc = SparkSession \
18     .builder \
19     .master("local[*]") \
20     .appName("API-Demo") \
21     .getOrCreate()
22
23 # Add Numerical Label for Emotions
24 emotion_key = {
25     "boredom": 0,
26     "love": 1,
27     "relief": 2,
28     "fun": 3,
29     "hate": 4,
30     "neutral": 5,
31     "anger": 6,
32     "happiness": 7,
33     "surprise": 8,
34     "sadness": 9,
35     "worry": 10,
36     "enthusiasm": 11,
37     "empty": 12,
38     "---": 13
39 }
40
```

¹⁹RESTful API is an interface that two computer systems use to exchange information securely over the internet.

```

41 # Initialize the AutoTokenizer
42 tokenizer = DistilBertTokenizer.from_pretrained("distilbert-base-multilingual-cased")
43
44 # Load Saved Models
45 model_en_rfc = PipelineModel.load("./models/model_en_rfc.model")
46 model_en_nb = PipelineModel.load("./models/model_en_nb.model")
47 model_en_lr = PipelineModel.load("./models/model_en_lr.model")
48 model_de_rfc = PipelineModel.load("./models/model_de_rfc.model")
49 model_de_nb = PipelineModel.load("./models/model_de_nb.model")
50 model_de_lr = PipelineModel.load("./models/model_de_lr.model")
51
52
53 app = Flask(__name__)
54 CORS(app) # Use the CORS class to enable CORS for the entire app
55 translator = Translator()
56
57 # Setup Emotion Key Reverse
58 emotions = {v: k for k, v in emotion_key.items()}
59
60 @app.route('/predict', methods=['GET'])
61 def transform_data():
62     start_time = datetime.datetime.now()
63     sentence_en = request.args.get('sentence_en')
64     sentence_de = request.args.get('sentence_de')
65
66     print(f"English: {sentence_en}")
67     print(f"German: {sentence_de}")
68
69     if sentence_en:
70         sentence_de = translator.translate(sentence_en, dest="de").text
71     elif sentence_de:
72         sentence_en = translator.translate(sentence_de, dest="en").text
73     else:
74         return jsonify({'error': 'No Sentence provided!'})
75
76     print(f"English: {sentence_en}")
77     print(f"German: {sentence_de}")
78
79     words_en = tokenizer.tokenize(sentence_en)
80     words_de = tokenizer.tokenize(sentence_de)
81
82     # Create English & German Dataframe
83     df_en_api = sc.createDataFrame([sentence_en, words_en], ["sentence", "words"])
84     df_de_api = sc.createDataFrame([sentence_de, words_de], ["sentence", "words"])
85
86     predictions_en_rfc = model_en_rfc.transform(df_en_api)
87     predictions_en_nb = model_en_nb.transform(df_en_api)
88     predictions_en_lr = model_en_lr.transform(df_en_api)
89     predictions_de_rfc = model_de_rfc.transform(df_de_api)
90     predictions_de_nb = model_de_nb.transform(df_de_api)
91     predictions_de_lr = model_de_lr.transform(df_de_api)

```



```

92
93     # Get End Time
94     end_time = datetime.datetime.now()
95     elapsed_time = (end_time - start_time).total_seconds()
96
97     #Build Response
98     resp = {
99         "sentence": {
100             "english": sentence_en,
101             "german": sentence_de,
102         },
103         "predictions": {
104             "en_rfc": emotions.get(predictions_en_rfc.collect()[0]["prediction"]),
105             "en_nb": emotions.get(predictions_en_nb.collect()[0]["prediction"]),
106             "en_lr": emotions.get(predictions_en_lr.collect()[0]["prediction"]),
107             "de_rfc": emotions.get(predictions_de_rfc.collect()[0]["prediction"]),
108             "de_nb": emotions.get(predictions_de_nb.collect()[0]["prediction"]),
109             "de_lr": emotions.get(predictions_de_lr.collect()[0]["prediction"]),
110         },
111         "metadata": {
112             "spark": sc.version,
113             "datetime": {
114                 "start": start_time,
115                 "end": end_time,
116                 "elapsedInSeconds": elapsed_time,
117             }
118         }
119     }
120
121     return jsonify(resp)
122
123 if __name__ == '__main__':
124     app.run(host='127.0.0.1', port=8080)
125

```
