# Sentiment Analysis Framework for Marathi Text

Domain: Natural Language Proessing

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***Abstract*—Sentiment Analysis is one of the most critical jobs for any language, as well as a key topic in Natural Language Processing that has made significant advances in recent years. Popular and commonly used languages like as English, Russian, and Spanish have a large number of language models and datasets accessible for these purposes. However, in Low Resource Languages such as Hindi and Marathi, research is lagging far behind. Marathi, India's third most spoken language, is one of the most widely spoken languages in the country. This is mostly spoken by Maharashtra residents. The use of language on internet platforms has grown exponentially during the last decade. Natural Language Processing (NLP) techniques for Marathi text, on the other hand, have gotten little attention.As a result, the goal of this research is to develop a framework that can be used to extract opinions from social media Marathi articles without the need for translations. Not only will you receive better results if you don't use translations, but you'll also obtain an error-free model that has solely been trained on the target language for the target task. For the job of opinion mining and classification, the multilingual model XLM-RoBERTa will be trained on the Marathi tweets dataset. For the purpose of opinion mining, we want to provide the outcomes of various XLM-R models over the Marathi tweets dataset.**

***Index Terms*—Sentiment Analysis, Low Resource Language, Marathi, XLM-R**

## I. Introduction

The USA elections of 2020 and the fake news that was spread during and after the presidential campaigns shows us the importance of social media companies in the fight against fake news. The Ability of Twitter to flag tweets considered as hateful or inciting violence was based on sentiment analysis of the tweets using Machine Learning models. However there has been miniscule research on opinion mining in low resource languages like Marathi, Gujarati, and other Indian languages. Social media users in India are currently mainly from the urban areas mainly using the English language. However, with the National Optical Fibre Mission and other initiatives to bring internet connectivity to rural areas, there is going to be a boom in the number of users using non-English native languages to text on social media. Hence the need for opinion mining in these languages is urgent. Marathi is the 3rd most spoken native language in India, with 83 million native speakers according to the 2011 census. Current best available models for Marathi text classification have been trained over news articles and news headlines data. This cannot give a very accurate analysis of the social media texts. We will create a framework where the language model trained on twitter data will be deployed and can be used by multiple people for generating opinions out of their Marathi text. In Marathi language the location of the words can be changed without changing the meaning of the sentence.

## II. Problem Definition

The current models and systems available are designed to analyze the data of tweets in the English language. The accuracy of data converted from regional languages to English and then performing opinion mining was found to be too low. Hence, we here propose to create a system that is capable of social media opinion mining in the Marathi language.

## III. Literature Review

Social Media plays a significant role in determining the opinion of people and hence is an important NLP task for detecting and analysing the text. This will help in knowing the polarity of texts and understanding people's opinions on various issues. The majority of existing works for sentiment analysis in the Marathi language have used a limited dataset based on news articles as in [1]. They achieve higher accuracy for sentiment analysis of news headlines and news articles, but the accuracy diminishes for non-news article. Hence, there is a need for using a wider dataset and training it on models which yield better results on low resource languages, like the XLM-R model.

There has been a tremendous rise in events of hate speech on social media, authors in [2] provide an effective neural network-based technique for the hostility detection in the low resource language Hindi text. It is very important to classify the social media texts in categories like very negative, negative, neutral, positive and very positive to locate the hostile texts. They have used word embeddings for deciding the polarity of texts as authors in [6] have shown that proper word embeddings can boost performances by a large margin. The dataset used for training was cleaned of any emojis, English language text along with white space removal, stemming, removal of stop words, removal of numbers, removal of URL links to ensure higher accuracy as shown by authors in [7] and [8] where they had performed sentiment analysis for the Hindi and the Manipuri language respectively. In sentiment analysis, there has been the problem of dealing with tweets and social

media texts where negation occurrence does not necessarily mean negation, authors in [9] have presented comprehensive research in the field of sentiment analysis by looking into tweet normalization and negation which are the critical aspects of NLP. In recent years educational and specialized web resources have seen heated discussions. People using these sites are characterized by restraint in statements and expressions of emotion characterised by ridicule, sharp jokes, provocative statements and hidden injections. Hence there is also a need for annotating these low toxic statements as done by authors in [3]. Hence we propose XLM-R based models for the task of opinion mining in Marathi language

## IV. Proposed Architecture

### A. Tokenization (Roberta)

Roberta Tokenizer is used for tokenizing the tweets before training of the models. It uses byte level BPE as a tokenizer. It treats spaces as parts of the tokens so it is treated differently at the front of a word and the back of a word. This tokenizer is derived from the GPT-2 tokenizer.

### B. XLM-RoBERTa – base

XLM-R is a transformer-based multilingual masked language model pre-trained on 2.5 TB of CommonCrawl data in 100 languages with base having 250M parameters, which obtains state-of-the-art performance on cross-lingual classification, sequence labeling and question answering. The base is trained over the BERT-base architecture along with XLM. The XLM-R outperforms other significant models by over 20% for the task of text classification due to the larger size of the training of the XLM-R [5]. We propose to fine-tune all the available XLM-R models over the Marathi tweets dataset and compare the accuracies achieved.

### C. XLM-RoBERTa – Large

XLM-R large is trained with 560M parameters and XL and XXL versions of XLM-R have been trained with 3.5B and 10.7B parameters in 100 languages. Large model has been trained with BERT-Large architecture with 250K being the vocabulary size. XXL is the largest XLM-RoBERTa model currently available that gives high accuracies for most of the tasks for most of the languages of the 100 available.

## V. Working

### A. Dataset

In this work, we used the publicly available L3CubeMahaSent [1] Twitter corpus, which is the first publicly available dataset in Marathi language for the task of Twitter Sentiment Analysis. This corpus was released in 2021 alongside their experiments on the baseline models available for sentiment analysis. This includes approximately 16000 Marathi tweets manually classified into the 3 classes. Our goal is tweet polarity classification, that is, classifying a tweet into positive, negative, or neutral classes. Training includes approx 12000 tweets, while testing and validation sets include 2250 and 1500 tweets each, which clearly shows the perfect balance of the classified tweets among them. So, there is lesser chance of a bias in the training and testing of the models.

### B. Data Preprocessing

The data that is fetched directly from twitter is not clean and contains many unwanted text and noise. This needs to be cleaned [7] [8] before putting the data under training for the models to properly understand the language we train it on.
Links: Every tweet scraped from any API contains the link to that tweet followed by the tweet itself. We removed all the links and URLs present in the tweets as they have no significance in our required task.
Hashtags and Mentions: Hashtags are words that are preceded by (symbol), these are used when referring to a known or popular topic or keyword. Hashtags serve as URL to a page displaying posts about that same topic. We removed all the hashtags except the one's in Marathi language as they might have a significant meaning in the tweet. So, in the Marathi hashtags, only the symbol was removed. Mentions are words that are preceded by @(symbol), containing another twitter user's username in the tweet body and are used when talking to or about someone. We removed all the mentions in the tweets as they serve no purpose in the sentiment analysis task.
Emojis: People these days use the social media creatively and this increases the usage of the emojis in the tweets, messages, and posts. Although these emojis can be replaced with its meaning in the English datasets, it is not possible to do so in Marathi yet. Hence, we completely removed all the emojis present in the tweets.
Spaces: The extra spaces from the tweets were removed and replaced with a single space.
Numbers and Punctuations: Numbers have no role in the sentiment analysis; hence numbers and the punctuations of the tweets were removed.

### C. Experimental Setup

We had divided the dataset into training, testing and validation sets and we used them for the respective parts. The testing part was used for the determination of the accuracies of the models mentioned below. We tokenize the data using the Roberta tokenizer and use it for the training purpose. The accuracies are tested over the models that are trained with 25 epochs over the same training set

## VI. Results

The results show us that Large variant of the XLM-RoBERTa performs the best over this Marathi dataset and has comparable results with other models as in Kulkarni et al [1]. The base variant of XLM-R performs good with 82.5%. Additionally our accuracy of 83.8% is the best accuracy possible for the task of sentiment analysis using XLM-R Large model for three class classification.

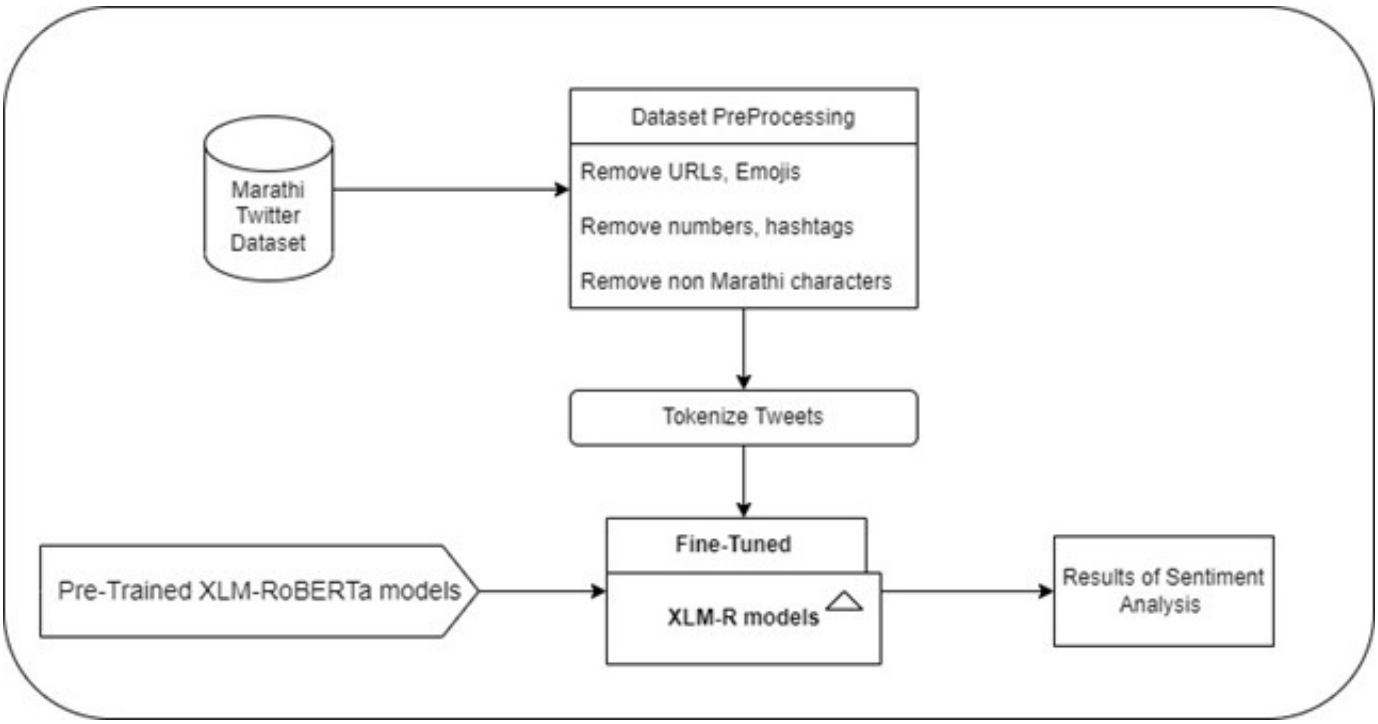


Fig. 1. Model Architecture

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