Social Media Data Analysis for Malayalam YouTube Comments: Sentiment Analysis and Emotion Detection using ML and DL Models

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Abstract

In this paper, we present a study on social media data analysis of Malayalam YouTube comments, specifically focusing on sentiment analysis and emotion detection. Our research aims to investigate the effectiveness of various machine learning (ML) and deep learning (DL) models in addressing these two tasks. For sentiment analysis, we collected a dataset consisting of 3064 comments, while for two-class emotion detection, we used a dataset of 817 comments.In the sentiment analysis phase, we explored multiple ML and DL models, including traditional algorithms such as Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbors (KNN), MLP Classifier, Decision Tree, and Random Forests. Additionally, we utilized DL models such as Recurrent Neural Networks (RNN),Long Short-Term Memory (LSTM) and Gated Recurrent Unit(GRU). To enhance the performance of these models, we preprocessed the Malayalam YouTube comments by tokenizing and removing stop words. Experimental results revealed that DL models achieved higher accuracy compared to ML models, indicating their ability to capture the complex patterns and nuances in the Malayalam language.Furthermore, we extended our analysis to emotion detection, which involved dealing with limited annotated data. This task is closely related to social media data analysis. For emotion detection, we employed the same ML models used in the sentiment analysis phase. Our dataset of 817 comments was annotated with two emotions: Happy and Sad. We trained the models to classify the comments into these emotion classes and analyzed the accuracy of the different models.

1 Introduction

Social media platforms have revolutionized the way people communicate and express their opinions. With the exponential growth of user-generated content, analyzing social media data has become essential for understanding public sentiment and emotional responses. In this context, YouTube, one of the most popular video-sharing platforms, provides a wealth of data in the form of user comments. Analyzing these comments can offer valuable insights into the sentiments and emotions of viewers, which can be utilized for various applications, such as content recommendation, user engagement, and market research.

This work focuses on social media data analysis for Malayalam YouTube comments, specifically targeting sentiment analysis and emotion detection. Malayalam, a Dravidian language predominantly spoken in the Indian state of Kerala, presents unique challenges due to its complex grammar and distinct linguistic features. Analyzing sentiments and emotions in Malayalam comments requires a deep understanding of the language's nuances and cultural context.The main challenge of the Malayalam language is the lack of an available annotated dataset(Soumya and Pramod, 2020).Therefore, we have begun our work by creating our own dataset.

The primary objective of this research is to explore the effectiveness of different machine learning (ML) and deep learning (DL) models in tackling sentiment analysis and emotion detection tasks for Malayalam YouTube comments. Sentiment analysis aims to classify comments as positive, negative, or neutral, providing an overall sentiment polarity associated with the content. On the other hand, emotion detection focuses on categorizing comments into predefined emotion classes, such as happiness, anger, sadness, or surprise,etc.

To conduct this study, we collected a sizable dataset of 3,064 comments for sentiment analysis and an additional 817 comments for two-class emotion detection. We employed various ML and DL models, including traditional algorithms such as Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbors (KNN), MLP Classifier, Decision Tree, and Random Forests. Additionally, we utilized DL models such as Recurrent Neural

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Networks (RNN), LSTM, and GRU. The dataset was preprocessed by tokenizing the comments and removing stopwords to enhance the models' performance.

The main focus of our investigation is to compare the accuracy of the ML and DL models in sentiment analysis and emotion detection tasks. We hypothesize that DL models will outperform ML models due to their ability to capture complex patterns and linguistic nuances present in the Malayalam language. The findings of this study will contribute to the growing field of social media analytics, providing valuable insights into the sentiment and emotional responses of YouTube users in the Malayalam language.

Overall, this work aims to shed light on the effectiveness of ML and DL models for social media data analysis of Malayalam YouTube comments, emphasizing the importance of accurately understanding sentiments and emotions expressed in regional languages. The outcomes of this study can benefit content creators, marketers, and researchers seeking to leverage social media data for decision-making and understanding user preferences in the context of Malayalam YouTube content.

2 Literature

Social media platforms have become prominent sources of user-generated content, providing vast amounts of data for analysis. With the increasing popularity of regional languages, there is a growing need to develop effective techniques for analyzing text data in languages other than English. In the context of Malayalam, a Dravidian language predominantly spoken in Kerala, India, social media data analysis using machine learning (ML) and deep learning (DL) models has gained attention. This literature review examines relevant studies focusing on social media data analysis of Malayalam text data, specifically employing ML and DL models.Most of the Malayalam Social Media Data analysis work is carried out in sentiment analysis problem.The table 1 below provides a literature review focusing on sentiment analysis in social media data analysis problems.

We conducted a survey on several social media data analysis problems, including offensive language identification, part-of-speech tagging, emotion detection, sarcasm detection, humor detection, and more, in various languages. The table 2 show some works related to these topics.

In summary, the literature review demonstrates a growing interest in social media data analysis of Malayalam text data using ML and DL models. Existing studies have explored sentiment analysis and emotion detection, highlighting the effectiveness of both traditional ML algorithms and advanced DL models in capturing sentiments and emotions expressed in Malayalam text. However, the focus has been on specific domains or platforms, such as news headlines, tweets, or movie reviews, leaving a gap in the analysis of Malayalam YouTube comments. This work aims to fill this gap by implementing sentiment analysis and emotion detection specifically for Malayalam YouTube comments using ML and DL models.

3 Objectives

The goals of this work is to explore the application of machine learning (ML) and deep learning (DL) models for social media data analysis of Malayalam text data, with a specific focus on sentiment analysis and emotion detection in Malayalam YouTube comments. The key objectives of this study are as follows:

- Implement sentiment analysis: Develop ML and DL models to classify Malayalam YouTube comments into sentiment categories, such as positive, negative, or neutral. Compare the performance of ML and DL models in terms of accuracy, precision, recall, and F1-score.

- Perform emotion detection: Train ML models to detect emotions expressed in Malayalam YouTube comments, such as happiness and sadness. Evaluate the performance of MLmodels in accurately identifying emotions.

- Compare ML and DL models: Compare the performance of ML models (such as KNN,SVM, Naive Bayes,MLP classifier,Decision Trees and Randm Forset) with DL models (such as RNN,LSTM and GRU) in sentiment analysis and emotion detection tasks. Assess the superiority of DL models in capturing the nuances of Malayalam language and achieving higher accuracy compared to ML models.

- Analyze the challenges and limitations: Identify the challenges and limitations specific to

Reference of the work.	Dataset	Algorithms Used	Metrics
(Soumya and Pramod, 2020)	3184 Malayalam tweets	NB,SVM,and RF	RF classifier with Unigram with Sentiwordnet including negation words, got the highest accuracy,95.6%
(Rahul et al., 2018)	1286 Malayalam sentences	CRF and SVM	Accuracy:52.75%
(Kumar et al., 2017)	12922 malayalam tweets	CNN,LSTM	LSTM with SELU achieved best results:F1-score:0.9823, Recall:0.9824,Precision:0.9823, Accuracy: 0.9824
(Pavan Kumar et al., 2021)	Youtube comments(codemix text),facebook posts etc	CNN,LSTM,Bi-LSTM	Bi-LSTM got highest accuracy
(Soumya and Pramod, 2022)	Malayalam Tweets	Hybrid Models-CNN with variants of RNN(LSTM,Bi-LSTM,GRU)	Hybrid models improve the performance of Sentiment Classification compared to baseline models LSTM, Bi-LSTM and GRU.
(Hande et al., 2021)	Code-mixed YouTube comments for Tamil, Malayalam, and Kannada languages.	Pretrained transformer-based models that have been used for both STL and MTL	Multi-task learning model can achieve high results compared with single-task learning while reducing the time and space constraints required to train the models on individual tasks.
(Thara and Poornachandran, 2022)	Malayalam – English code-mixed data set	DL models-uni-/bi-directional, hybrid,and transformer models	F1-Score- 0.76

Table 1: Literature on sentiment Analysis.

Reference of the work	Topic and Dataset	Algorithms Used	Metrics
(Sasidhar et al., 2020)	Emotion Detection,12000 Hindi-English code-mixed texts	1D-CNN,Bi-LSTM,CNN-LSTM,CNN-BiLSTM	CNN-BiLSTM gave better performance with 83.21% classification accuracy
(Kumar et al., 2019)	POS Tagger,9915 Malyalam Tweets	RNN,GRU,LSTM, and bidirectional LSTM	GRU model at word level gave the highest f1-measure of 0.9254;at character-level,the BiLSTM model gave the highest f1-measure of 0.8739
(Sreelakshmi et al., 2021)	Offensive Language Identification, code-mixed sentences	Hybrid network models with Bi-LSTM and Bi-RNN	Hybrid network exhibited better training performance.
(Al-Ghadhban et al., 2017)	Sarcasm Detection,Arabic tweets	Weka classifier model	Precision-0.659,Recall- 0.710,F-score-0.676
(Mao and Liu, 2019)	Humor Detection,24000 English tweets	BERT-based approach	Accuracy-0.822
(Dhanya and Balakrishnan, 2022)	Offensive speech Detection, Malayalam-English Code Mixed Data	SVM,logistic regression,K-NN,random forest and XGBoost	XGBoost achieved good results with 80% accuracy and with high precision, recall and F1-score.

Table 2: Literature on different social media data anlaysis

sentiment analysis and emotion detection in Malayalam YouTube comments.

By achieving these objectives, this work aims to contribute to the field of social media data analysis by providing insights into the effectiveness of ML and DL models for sentiment analysis and emotion detection in the context of Malayalam YouTube comments. The findings can inform decision-making processes, content recommendation systems, and user engagement strategies for regional language-based social media platforms.

4 Theoretical Background

4.1 Social Media Data Analysis

Social media platforms have become a treasure trove of user-generated content, offering valuable insights into user opinions, sentiments, and emotions. Social media data analysis involves extracting, processing, and analyzing this vast amount of data to gain valuable insights(Rahul et al., 2018). It enables researchers and organizations to understand user behavior, preferences, and trends, and make data-driven decisions.

4.2 Sentiment Analysis

Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique that aims to identify and extract subjective information from text data. It involves determining the sentiment or polarity associated with a particular piece of text, such as positive, negative, or neutral. Sentiment analysis has gained significant attention in recent years due to the widespread use of social media platforms and the need to understand public opinion and sentiment towards various entities, including products, services, and events. Various approaches can be employed for sentiment analysis, including rule-based methods, lexicon-based methods, and machine learning-based methods(Nandwani and Verma, 2021). Rule-based methods utilize predefined linguistic rules and patterns to determine sentiment. Lexicon-based methods rely on sentiment lexicons or dictionaries containing words with associated sentiment scores. Machine learning-based methods involve training models on labeled datasets to learn patterns and classify text based on sentiment.

4.3 Emotion Detection

Emotion detection is a subfield of affective computing that focuses on recognizing and classifying emotions expressed in text, speech, or other forms of data. Emotions are complex psychological states that play a crucial role in human communication and decision-making. Emotion detection aims to automatically identify and categorize emotions such as happiness, anger, sadness, fear, surprise, and disgust from textual data(Sasidhar et al., 2020). Similar to sentiment analysis, emotion detection can be approached using different techniques. These include lexicon-based methods, machine learning-based methods, and deep learning-based methods. Lexicon-based methods utilize emotion lexicons containing words and their associated emotional labels. Machine learning-based methods involve training classifiers on labeled datasets, where features are extracted from the text data to predict emotions. Deep learning-based methods, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), can capture the contextual and sequential dependencies in the data, leading to improved emotion detection performance.

4.4 Machine Learning (ML) Models

Machine learning models are computational algorithms that can learn from data and make predictions or decisions without being explicitly programmed. ML models have been widely used in various NLP tasks, including sentiment analysis and emotion detection. Traditional ML algorithms, such as Support Vector Machines (SVM),KNN,MLP Classifier,Decision Tree, Naive Bayes, and Random Forests, have been applied successfully to sentiment analysis and emotion detection tasks. These models require feature engineering, where relevant features are extracted from the text data using TF-IDF feature extraction method(Soumya and Pramod, 2020) and used as input to the ML algorithms.

4.5 Deep Learning (DL) Models

Deep learning models are a subset of ML models that utilize artificial neural networks with multiple layers to automatically learn hierarchical representations from data. DL models have demonstrated remarkable performance in various NLP tasks, surpassing traditional ML algorithms(Pavan Kumar et al., 2021). In sentiment analysis created DL models, such as Recurrent Neural Networks (RNNs),LSTM, and GRU.

4.6 Malayalam Text Data

Malayalam is a Dravidian language predominantly spoken in the Indian state of Kerala. Analyzing sentiment and emotions in Malayalam text data presents unique challenges due to the language's specific linguistic features, grammar, and cultural nuances.The main challenge in Malayalam is the scarcity of annotated data(Soumya and Pramod, 2020). Therefore, we created our own dataset and tackled two problems using a small dataset. We are continuously working to expand our dataset size.

4.7 Evaluation Metrics

In sentiment analysis and emotion detection tasks, evaluation metrics are used to assess the performance of the models. Common metrics include accuracy, precision, recall, F1-score, and confusion matrices. Accuracy measures the overall correctness of predictions, while precision and recall provide insights into the models' ability to correctly identify specific sentiment or emotion categories. F1-score balances precision and recall, offering a single metric to evaluate model performance.

5 Methodology

5.1 Dataset Collection and labelling

The first step in the methodology involves gathering a Malayalam YouTube comment dataset for sentiment analysis and emotion detection. For this purpose, we developed a web scraping program to retrieve YouTube comments. A total of 7,500 YouTube comments were extracted from a variety of videos using automated web scraping techniques. From this collection, 3,064 comments were manually annotated to capture distinct sentiments for sentiment analysis, while 817 comments were assigned different emotions for emotion detection. The annotation process is being conducted by a team of three individuals to ensure accuracy; the final labels will be established after completion by all three team members. Due to the meticulous nature of this process, it is time-consuming, and thus, the annotation is ongoing. Currently, 3,064 comments have been labeled for sentiment analysis and 817 comments for emotion detection. Consequently, we have employed these labeled datasets for our study.

5.1.1 Data Labelling for sentiment analysis

The dataset was labeled or annotated for sentiment analysis. It was annotated with different sentiments, including positive, negative, and neutral. A total of 3,064 comments were labeled by three different individuals, and the majority vote was taken as the final label. To facilitate dataset labeling, we created a user interface using recat for easy annotation. The Fig. 1 shows a screenshot of the user interface. Table 3 shows the count of comments labeled with different sentiments.With this 3064 sentiments annotated dataset,we have created different ML and DL models.

Sentiments	number of comments
Positive	1548
Negative	575
Neutral	941
Total	3064

Table 3: count of different sentiments

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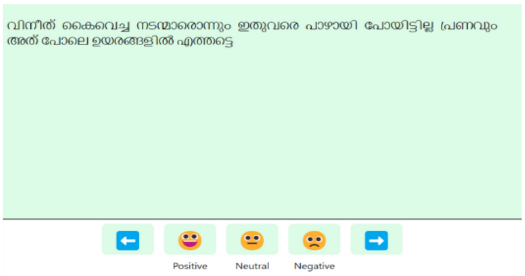

Figure 1: UI for Labelling Sentiment Analysis

5.1.2 Data Labelling for Emotion Detection

The dataset was labeled or annotated for Emotion Detection. Out of 7500 comments, 1000 comments were labeled with 10 different emotions, including Happy, Sad, Anger, Fear, Surprise, Affection/Love, Abusive, Sarcasm, Humor, and Excitement(Sasidhar et al., 2020). Each comment was labeled by three individuals, and the target label was determined based on majority votes. Data labeling was conducted through online and offline modes. Online modes included WhatsApp polls, Google Forms, and Google Sheets, while offline mode involved using hard copies of the form.

The Fig. 2 shows a screenshot of the WhatsApp poll used for annotation.Table 4 shows the count of comments labeled with different sentiments.The Fig. 3 shows a screenshot of the diferent emotions labelled comments.Due to the limited number of annotated samples per emotion, we have currently worked with two classes: happy and sad. We have implemented a two-class emotion detection using ML algorithms.

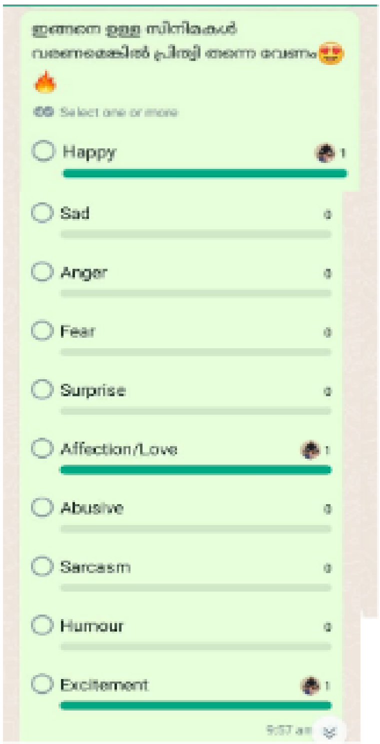

Figure 2: WhatsApp poll for Labelling

Emotions	number of comments
Happy	417
Sad	400
Anger	50
Fear	10
Surprise	20
Affection/love	100
Abusive	15
Sarcasm	10
Humour	25
Excitement	30
Total	1000

Table 4: count of different emotions

Emotions labelled comments

Sl No.	Comments	(1) Happy	(2) Sad	(3) Anger	(4) Fear	(5) Surprise	(6) Affection/	(7) Abusive	(8) Sarcasm	(9) Humour	(10) Exciteme
1	ദൈവത്തെ ഓർത്തു ഇനി സം.. വിധാനം ചെയ്യരുത് 🙏🙏🙏മോഹൻലാലിനോട് ഇഷ്ടം ഉള്ളത് കൊണ്ടാണ് ഇറങ്ങി പോകാഞ്ഞത് 🙏🙏	0	1	1	0	0	1	0	0	0	0
2	തിയേറ്ററിൽ ആളുകൾ ഉറങ്ങിയാണല്ലോ ആറാട്ട് നെ സ്വീകരിച്ചത് 😄😄😄😄	0	0	0	0	0	0	0	1	1	0
3	അപ്പോ തുടങ്ങിയല്ലേ നെയ്യാറ്റിൻകര ഗോപന്റെ ആറാട്ട് 🔥🔥	1	0	0	0	0	1	0	0	0	1
4	ആർക്കോ വേണ്ടി കോമാളിത്തരം കാണിക്കുന്ന സൂപ്പർ സ്റ്റാറുകളെക്കാൾ എത്രയോ മുകളിൽ ആണ് പ്രിഥ്വിരാജ്..👍👍👍	1	0	0	0	0	1	0	0	0	0
5	Adipoli movie 5/5. Unexpected climax👏	1	0	0	0	0	1	0	0	0	1

Figure 3: Emotions labelled comments

5.2 Data Preprocessing

Once the dataset is collected, it needs to be preprocessed to enhance the performance of the sentiment analysis and emotion detection models. Preprocessing steps may include tokenization, removing stop words, stemming or lemmatization, and handling special characters or emoticons specific to the Malayalam language(Rahul et al., 2018). This ensures that the text data is in a suitable format for further analysis.

5.3 Feature Extraction

In sentiment analysis and emotion detection, relevant features need to be extracted from the preprocessed text data. For sentiment analysis, the TF-IDF feature extraction method(Soumya and Pramod, 2020) is used in the creation of various ML models, while the Text-to-Sequence and Word2Vec methods are employed for creating DL models.The TF-IDF feature extraction method is also utilized in emotion detection with ML models.

5.4 Machine Learning Models

For sentiment analysis and emotion detection, ML models can be employed.The dataset was split into 80% training and 20% testing data, and various ML models were created, including NB, KNN, SVM, MLP classifiers, Decision Tree, and Random Forest.

5.5 Deep Learning Models

Sentiment analysis was implemented using different Deep Learning algorithms on the same dataset. The dataset was split into 80% training and 20% testing data, and various DL models, including DNN, RNN, LSTM, and GRU, were created(Kumar et al., 2017).These models can automatically learn representations and patterns from the text data.Pretrained word embeddings such as Word2Vec and feature extraction methods like text-to-sequence were utilized for implementing DL models.

5.6 Model Training and Evaluation

The ML and DL models are trained on the labeled dataset, with sentiment labels for sentiment analysis and emotion labels for emotion detection. The dataset can be divided into training, validation, and test sets to assess the models' performance. Accuracy, precision, recall, F1-score, and confusion matrices are common evaluation metrics. The models can be fine-tuned and retrained as necessary to achieve the best performance.

5.7 Performance Comparison

The performance of the ML and DL models is compared in terms of accuracy, precision, recall, and F1-score. The focus is on evaluating the performance of DL models against traditional ML models, particularly in terms of their ability to handle the nuances and complexities of the Malayalam language.

6 Experimental results and discussion

Sentiment analysis and emotion detection in our work are carried out using machine learning (ML) and deep learning (DL) techniques, implemented using the Python programming language.

6.1 Sentiment Analysis Results

For sentiment analysis of Malayalam YouTube comments, we implemented both machine learning (ML) and deep learning (DL) models. The ML models included NB, KNN, SVM, MLP classifiers, Decision Tree, and Random Forest, while the DL models comprised RNN,LSTM,and GRU.

6.1.1 Experimental results of sentiment analysis using ML Models

20% of the dataset, which consisted of 613 comments, was used for evaluating different ML models. The figures below show the confusion matrix of the different models using the same test data.The Fig. 4, 5,shows confusion matrix of different ML Models.

The table 5 displays the performance metrics of various ML models, including accuracy, precision, recall, and F1 score. it is clear that the MLP classifier and KNN with 15 neighbors achieved the highest accuracy.

Models	Accuracy	Precision	Recall	F1-Score
NB	43.72	0.4198	0.4184	0.410
KNN	54.32	0.4831	0.4451	0.4448
SVM	50.57	0.1711	0.3312	0.2256
MLP Classifier	54.32	0.4831	0.4451	0.4448
Decision Tree	49.27	0.4227	0.4037	0.4012
Random Forest	51.71	0.4249	0.3668	0.3177

Table 5: Performance Metrics of SA using ML Models

6.1.2 Experimental results of sentiment analysis using DL Models

20% of the dataset, which consisted of 613 comments, was used for evaluating different DL models.The table 6 displays the performance metrics of various DL models with text-to-sequence feature extraction methods,including accuracy, precision, recall, and F1 score.From the performance metrics table, it is clear that the GRU model achieved an accuracy of 54.21%, which is higher than that of the simple RNN and LSTM models.

Models	Accuracy	Precision	Recall	F1-Score
Simple RNN	52.23	0.4595	0.4470	0.4478
LSTM	52.89	0.4618	0.4471	0.4484
GRU	54.21	0.4717	0.4275	0.4189

Table 6: Performance Metrics of SA using DL Models

The table 7 displays the performance metrics of various DL models with Word2Vec,including accuracy, precision, recall, and F1 score.From the performance metrics table, it is clear that the LSTM model achieved an accuracy of 52.40%, which is higher than that of the simple RNN and GRU models.

Models	Accuracy	Precision	Recall	F1-Score
Simple RNN	49.26	0.4173	0.4072	0.4047
LSTM	52.40	0.4705	0.4400	0.4435
GRU	51.40	0.4501	0.4264	0.4273

Table 7: Performance Metrics of SA using DL

6.2 Emotion Detection Results

From the 1000 comments labelled with different emotions, 817 comments were selected for two-class emotion classification (happy and sad). We implemented various ML models for this task, including NB, KNN, SVM, MLP classifier, Decision Tree, and Random Forest. TF-IDF feature extraction was used to extract features.20% of the data, specifically 164 comments, were reserved for testing the different ML models.The table 8 displays the performance measures of various ML models, including accuracy, precision, recall, and F1 score. it is clear that the MLP classifier achieved an highest accuracy of 81.71%.

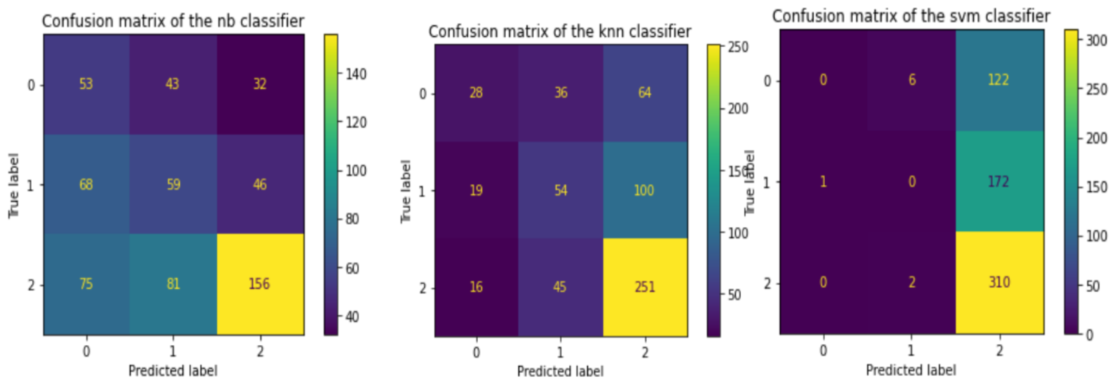

Figure 4: Confusion Matrix of NB,KNN and SVM

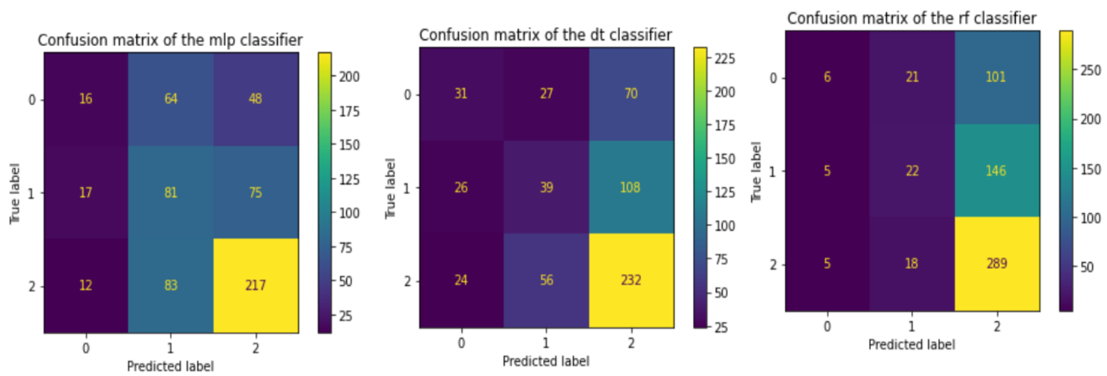

Figure 5: Confusion Matrix of MLP Classifier,Decision Tree and RF

Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**
NB	76.22	0.5221	0.5157	0.5180
KNN	73.78	0.4913	0.5005	0.4958
SVM	78.05	0.0.5556	0.5229	0.5178
MLP Classifier	81.71	0.5516	0.5520	0.5485
Decision Tree	68.90	0.4757	0.4626	0.4603
Random Forest	74.39	0.5360	0.4970	0.4895

Table 8: Perormance Metrics of Emotion Detection

7 Conclusion

In this paper addresses the challenges posed by the unavailability of annotated datasets for the Malayalam language in the field of natural language processing (NLP). To overcome this challenge, we created our own dataset with manual annotation and focused on two social media problems: sentiment analysis and emotion detection.For sentiment analysis, we utilized a dataset of 3064 annotated comments and implemented various machine learning (ML) and deep learning (DL) models. Among the ML models, MLP classifier and KNN with 15 neighbors demonstrated the highest accuracy. On the other hand, among the DL models, GRU and LSTM exhibited the highest accuracy. ML models were trained using TF-IDF feature vectorization, while DL models utilized Word2Vec embeddings.Additionally, we implemented two-class emotion detection using ML models, with MLP classifier achieving the highest accuracy.As part of our future work, we aim to increase the size of our dataset and implement more transformer models to further enhance the accuracy of our models.Overall, this research highlights the importance of creating annotated datasets for under-resourced languages like Malayalam and demonstrates the effectiveness of ML and DL models in addressing sentiment analysis and emotion detection tasks. The findings provide valuable insights for future studies in NLP for the Malayalam language and contribute to the growing body of research in this field.

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