Application of Nepali Large Language Models to Improve Sentiment Analysis

Shushanta Pudasaini
Institute of Engineering, Pulchowk, Nepal
shushanta574@gmail.com

Sunil Ghimire
Fusemachines Pvt. Ltd
Nepal;info@sunilghimire.com.np

Prabhat Ale
Fusemachines Pvt. Ltd, Nepal
srv.ale52@gmail.com

Aman Shakya
Institute of Engineering, Pulchowk
Nepal;aman.shakya@ioe.edu.np

Prakriti Paudel
Advanced College of Engineering and Management, Balkhu, Nepal
iprakrity.paudel0@gmail.com

Basanta Joshi
Institute Of Engineering, Pulchowk
Nepal;basanta@ioe.edu.np

ABSTRACT

With the rise in internet usage, Nepali individuals have left a flood of opinionated comments in their language on YouTube and other social media sites. Such remarks can be subjected to sentiment analysis, which can be useful for both research and business purposes. Such sentiment analysis models can be extremely useful in understanding the user's expectations towards the product which can uplift the business of any organization. Similarly, with the rise of Large Language models in the NLP space, there are several large language models pre-trained on the BERT architecture upon the Nepali text corpus. This research focuses on developing a benchmarking dataset for sentiment analysis in the Nepali language and demonstrating how large Nepali language models can be used to improve the results on downstream NLP tasks like sentiment analysis on such benchmark datasets. This paper describes an approach to how proper embeddings for a Nepali sentence can be extracted from the pre-trained Nepali language models. The comparison of transfer learning applied to the dataset on different machine learning and deep learning algorithms has been done in this study. From this experimentation, a state-of-the-art sentiment analysis model in the Nepali language with an F-score of 0.88 has been developed.

CCS CONCEPTS

• **Computing Methodologies**; • **Machine Learning**; • **Machine Learning Algorithms**;

KEYWORDS

Natural Language Processing, Sentiment Analysis, Bidirectional Encoders for Representational Transformers, Transfer Learning, Large Language Models, Machine Learning Algorithms, Finetuning

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1 INTRODUCTION

Sentiment analysis is the task of determining the emotional tone of a piece of text, such as whether it is positive, negative, or neutral. It is a valuable tool for understanding public opinion, customer feedback, and social media sentiment. It falls under natural language processing which identifies and extracts the subjective information from the given textual documents and determines the contextual polarity of given sentences. With the recent increase of blogs, social media networks, and video streaming websites; a lot of reviews, comments, and ratings are expressed on these platforms.

This rise of opinionated textual data on the above platforms can be used to identify the sentiment of users on various topics and make a decision based on users' sentiments. The penetration of smartphones to Nepalese users has certainly grown over the decades allowing users to interact with social media platforms and leave their comments, and opinions in the Nepali language. Nepali language is written in Devanagari script and has its own grammatical structure, vocabulary, and semantics [1]. Similarly, with the rise in popularity of large language models such as chatGPT from OpenAI and Bard from Google, Nepali researchers have been building pre-trained language models using the BERT and GPT architecture. The knowledge learned by these pre-trained language models can be used for several downstream Natural Language Processing (NLP) tasks such as sentiment analysis and Named Entity Recognition (NER) [2].

This study stands out from traditional sentiment analysis methods that rely on TFIDF and count vectorizers by employing a novel strategy that uses transfer learning to extract features from Nepali large language models. This study also highlights the curation of specialized datasets by collecting comments from various Nepali YouTube videos, as well as proposing a new approach for extracting features from Nepali sentence embeddings. Moreover, the research makes a noteworthy contribution by comparing various open-source Nepali language models. This unique aspect of the study involves identifying the most successful model for sentiment classification on a custom dataset, filling a gap in previous research where such comparisons were lacking. The major contributions from this research are listed below.

- Manually collect a dataset; scraping from various YouTube videos and labelling them.
- Develop a data scraping module for the Nepali language.
- Develop a novel approach for extracting Nepali sentence embeddings from BERT-based pre-trained models.
- Comparison of results from transfer learning applied on open-source Nepali pre-trained language models.
- Present a state-of-the-art model for sentiment analysis on the Nepali language based on Nepali pre-trained language models.

This paper's findings hold significant implications for businesses operating in the Nepali market, enabling them to:

- By harnessing the power of sentiment analysis, businesses can differentiate themselves from competitors, gain a deeper understanding of their target audience, and make informed decisions that drive business growth and success.
- By understanding customer sentiment, businesses can proactively address customer concerns, improve product offerings, and tailor marketing campaigns, ultimately enhancing customer experience and loyalty.
- Sentiment analysis can inform strategic decision-making, enabling businesses to identify market trends, optimize resource allocation, and capitalize on emerging opportunities.

2 LITERATURE REVIEW

Several research works have been done recently in the Nepali NLP space. Researchers have been focusing on building Nepali textual corpus and large language models based on recent architectures such as Bidirectional Encoder Representational Transformers (BERT) and Generative Pretrained Transformers (GPT) [3]. Research on sentiment analysis in the Nepali language using traditional features engineering approaches such as Word2Vec and Fasttext and classification algorithms such as Support Vector Machines (SVM) are abundant. However, the gap persists in applying the knowledge learned from large pre-trained language models in the Nepali language for such sentiment analysis tasks.

Several research studies have been done in sentiment analysis on English datasets. Alaa Hamouda et al. developed a machine learning-based senti word lexicon (MLBSL) to solve the sentiment analysis problem in the English language [4]. Hidden Markov Models were used to solve the sentiment analysis for the Amazon review dataset [5]. Regularized Locality Preserving Indexing (RLPI) has been used for feature extraction techniques for sentiment analysis on IMDb reviews [6]. Natural Sentiment Strength (NSS) values were used to identify the sentiment score in the sentiment analysis of English sentiment data [7]. Similarly, algorithms such as FireFly (FF) and Levy Flights (FFL) algorithms have been used for the feature engineering of different web based reviews for sentiment analysis [8].

Sujan Tamrakar et al have implemented sentiment analysis on Nepali news media texts [9]. Their architecture consisted of data collection, preprocessing, Anaphora Resolution, and Sentiment Analysis. For the data collection step, news articles were scraped from four online news portals. Collected datasets were cleaned via article cleaning subcomponents and further lemmatized to split a word into root forms and remove unwanted suffixes under the preprocessing step. Part of Speech(POS) tagging, NER tagging, and Lappin and Leas's algorithm for anaphora resolution were performed on the collected datasets to increase the overall accuracy of the system. Word2Vec and FastText were used for feature extraction using Skip Gram architecture. Due to low datasets, the sentiment analysis was trained on the Support Vector Machine, Decision Tree, and Random Forest where the Support Vector Machine had a better overall score. SVM had an F1 score of 80.2 and 78.7 on Word2Vec and FastText respectively. A total of 3490 sentences were scraped for this research method out of which 2676 datasets were positive and 814 were negative.

O.M. Singh et al performed aspect-based sentiment analysis on a dataset scraped from YouTube comments [10]. They used the BRAT annotation tool to annotate comment datasets at the sentence level where Noun phrases were assumed as an aspect term. Annotation was performed according to the annotation guidelines. Two different annotators annotated the sentence's polarity and their inter-annotator agreement was found to be 0.703. Upon analysis of the corpus, the collected dataset had diverse use of language on social media platforms. The ratio of use of English words to Nepali words was around 0.0125 and found that Negative sentiment was directed towards politicians or persons but not toward any organizations. They have used the BiLSTM+CRF model for aspect term extraction tasks and BiLSTM+CNN for sentiment polarity classification. A total of 3068 comments were collected from various YouTube channel videos of which train, test, and validation data were split into 80%, 10%, and 10% respectively. They trained the dataset on 300-dimensional skip-gram fast text word embeddings using Gensim to generate word embeddings. The overall F1 score of aspect term extraction and sentiment classification was 57.98 and 81.6 respectively.

Ashok Kumar Pant et al implemented sentiment analysis on Nepali Movie reviews [11]. They collected 500 Nepali movie review datasets from online sources. Preprocessing of data is performed to clean and extract features from the comments. TF-IDF vectorizer is used to extract word embeddings for the collected datasets and implemented Naive Bayes Classifier for the sentiment analysis. From the given dataset they had Precision, Recall, and F-Score of 79.23%, 78.57%, and 78.9% respectively. They have presented that with an increase in datasets and other machine learning algorithms like SVM, Neural Networks, and Fuzzy logic the performance of the system could be improved.

Evaluation and testing of the accuracy, inference time, and model training time are mostly done to validate the working of the SMS spam classification algorithm. Performance evaluation of sentiment analysis on text and emoji data was done using transfer learning, explainable AI, and distributed models [12].

3 METHODOLOGY

The process of building data and transfer learning on the pre-trained Nepali large language models is discussed in the below sections.

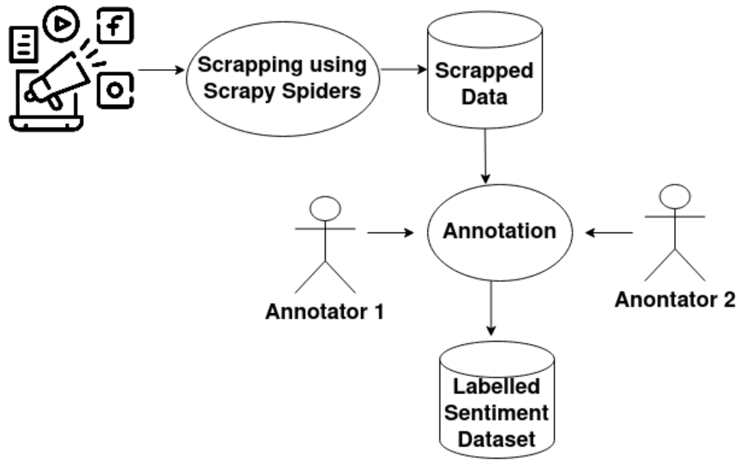

Figure 1: Data Collection Procedure

3.1 Building Nepali Sentiment Analysis Labeled Dataset

The dataset for the Nepali sentiment analysis is mainly scraped from YouTube video comments. A scraping algorithm to scrape YouTube comments that are only written in the Nepali language was developed. The Scrapy framework of Python was used to build spiders that would go through a list of YouTube video URLs and scrape all the comments in those videos. Only comments in the Nepali language were required, thus a simple Python module was developed to detect the language of the text. The module was developed using the Langdetect library of Python. The comments scrapped were filtered using the module to obtain those comments that are only in the Devanagari language. Two data annotators then labeled these filtered comments in a month. The overall process of the data collection is represented in Figure 1.

Various comments with topics ranging from politics, news, gadgets reviews, food, travel, share markets, etc were scraped and collected. A total of 7249 comments were scraped from which 3089 negative sentiment comments and 4160 positive sentiment comments were annotated. Here for the labeling process, sentences with negative sentiment have been labeled as 0 whereas those with positive sentiment have been labeled as 1. The final labeled dataset was then split into the training set and a testing set for training and evaluation respectively. The dataset is made open source so that other researchers can evaluate other algorithms on the dataset and improve the results even further. The dataset can be accessed through this GitHub repo.

3.2 Generating embeddings for Nepali sentences

Sentence embeddings are vector representations of sentences that capture their semantic meaning [13]. Those embeddings can be used for a variety of tasks, such as natural language understanding, machine translation, and question-answering [14].

In this paper, we propose a method for generating embeddings of Nepali sentences from any pre trained Nepali language models. The Nepali sentence is first passed to the pre-trained models. Then, the sentence embeddings are generated by summing the last 4 layers of the model's output.

To avoid the explicit for loops and list comprehensions, the following code was used:

$$sum\_last\_4\_layers = tosum\_last\_4\_layers =$$
$$torch \cdot stack\,(enc\_layers\,[-4:]) \cdot sum\,(0)$$
$$rch \cdot stack\,(enc\_layers\,[-4:]) \cdot sum\,(0)$$

This code creates a single tensor that contains the sum of the last 4 layers of the model's output. The size of this tensor is equal to the length of the sentence times the embedding dimension [15]. To get a single (i.e., pooled) vector, max-pooling or average-pooling could be used. Max-pooling takes the maximum value from each dimension of the tensor, while average-pooling takes the average. The max-pooling performed better than the average pooling for Nepali sentences during the experiment. This is likely because max-pooling is more robust to noise and outliers. The overall process of generating embeddings from the pre-trained models is shown in Fig 2

3.3 Comparison of transfer learning applied on Nepali pre-trained language models using Nepali sentiment data

Researchers in the Nepali NLP domain have been developing several large language models. Most of them are trained in BERT architecture with the task of Masked Language Modeling (MLM)[16]. Such BERT-based large language models can understand the Nepali language. This model can be used to generate embeddings of each and every token in the Nepali language. Such embeddings can be used as a feature for classification tasks such as Sentiment Analysis [17].

The open-source large language models were searched over the HuggingFace platform. The HuggingFace platform is the most popular platform for accessing NLP-based public models worldwide [18]. Based on the number of downloads, four models were selected

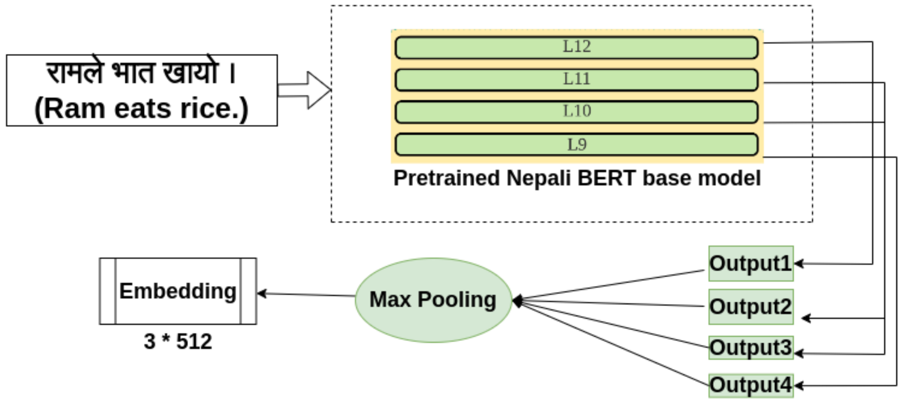

Figure 2: Embedding Generation Procedure

and experimentations were performed. The model descriptions are given below.

3.3.1 Distil BERT base Nepali. The DistilBERT-base-Nepali model is a Transformer-based language model that is pre-trained on a dataset of over 13 million Nepali text sequences [19]. It is a distilled version of the BERT model, which means that it is smaller and faster, but still retains a lot of the performance of the original model. The model is fine-tuned on Nepali language-focused downstream tasks such as sequence classification, token classification, and question answering. It can be used for a variety of tasks, such as text classification, Named Entity Recognition, and Machine Translation. The model is available on the Hugging Face Hub, where it can be downloaded and finetuned for custom tasks. It is also available as a hosted inference API, which means that it can be used by researchers to make predictions without having to download or install a model. The distilBERT-base-Nepali model is a powerful language model that can be used for a variety of tasks.

3.3.2 NepaliBERT.. NepaliBERT is a Transformer-based language model for Nepali, and it has been shown to outperform other models on a variety of tasks, such as text classification, named entity recognition, and question answering. The model is trained using the masked language modelling (MLM) objective. This means that the model is trained to predict the missing words in a sequence of text. The model has 137M parameters. This is a measure of the complexity of the model. The model was trained on a dataset of over 13 million Nepali text sequences. This dataset was collected from a variety of sources, such as news articles, social media posts, and books. Here are some of the advantages of using NepaliBERT:

The model is a powerful language model that can be used for a variety of tasks.

- It is a large model, so it has the capacity to learn the nuances of the Nepali language.
- It is trained on a large dataset of Nepali text sequences, so it is more likely to be familiar with the different ways that Nepali is used.
- It has been fine-tuned on a variety of tasks, so it can be used for a wider range of applications.

Here are some of the limitations of the model:

- It is a large model, so it requires a lot of computing resources to train and fine-tune.
- It is trained on a dataset of Nepali text sequences, so it may not perform well on text from other languages.
- It is only trained on a block size of 512 tokens, so it may not perform well on shorter sequences.

Overall, the NepaliBERT model is a powerful language model that can be used for a variety of NLP downstream tasks.

3.3.3 NepBERTa. NepBERTa is a Transformer-based language model pre-trained on Nepali text sequences. It is a newer model than NepaliBERT and has been shown to outperform it on a variety of tasks. The model is trained using the masked language modelling (MLM) objective, as well as the next sentence prediction (NSP) objective. This means that the model is trained to predict the missing words in a sequence of text, as well as to predict the next sentence in a sequence of sentences [20]. The model has 110M parameters, which is a measure of the complexity of the model. It was trained on a dataset of over 13 million Nepali text sequences, which were collected from a variety of sources, such as news articles, social media posts, and books. The NepBERTa model has been shown to outperform NepaliBERT on a variety of tasks, such as named entity recognition (NER) and question answering (QA). This is because it has been trained on a more recent dataset of Nepali text sequences and has been shown to achieve better results on these tasks. The NepBERTa model is still a relatively new model, so it has not been as widely tested as other models. However, it is a promising model that has the potential to be a valuable tool for a variety of tasks in the Nepali language.

3.3.4 nepaliBERT.. The nepaliBERT model is a Transformer-based language model that is pre-trained on a dataset of over 13 million Nepali text sequences. It is a state-of-the-art language model for the Nepali langauge, and it has been shown to outperform other models on a variety of tasks, such as text classification, named entity recognition, and question answering. The model is trained using the masked language modelling (MLM) objective. This means that the model is trained to predict the missing words in a sequence

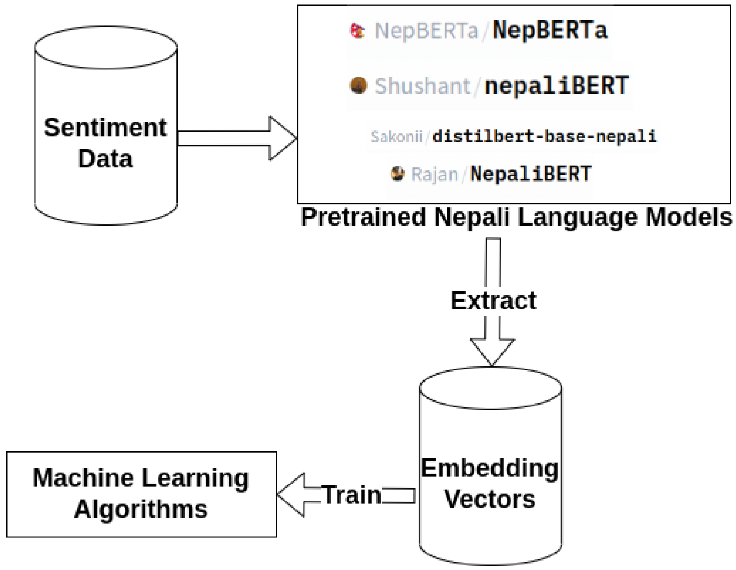

Figure 3: Transfer Learning Methodology

of text. The NepaliBERT model has been shown to outperform other models on a variety of tasks, such as text classification, named entity recognition, and question answering. This is because it has been trained on a large dataset of Nepali text sequences and has been shown to achieve better results on these tasks [21]. The NepaliBERT model is a powerful language model that has the potential to be a valuable tool for a variety of tasks in the Nepali language. It is a good choice for tasks where you need a model that can perform well on a variety of tasks and is familiar with the nuances of the Nepali language. The pre-trained language model has been open-sourced in HuggingFace and Github and fellow researchers can use the model for every downstream Nepali NLP task.

The embeddings of the sentences in our sentiment analysis data were generated from these open-source models using the approach mentioned above. These embeddings generated had been used as features for text classification to solve the sentiment analysis problem. The resulting models obtained from transfer learning of these models were evaluated in the testing set of our dataset. The results from each model have been compared and the best performing large language model in Nepali language has been declared in this paper. The overall procedure of applying transfer learning has been explained in Fig 3.

4 RESULTS

The results of the application of transfer learning on the open-source pre-trained large language models have been discussed in this section. The evaluation metrics such as precision, recall, and f-score have been recorded from training each of the models. The embeddings calculated from the large pre-trained Nepali language models listed above were used as features and further trained on the following machine-learning algorithms.

- Support Vector Classifier (SVC)
- Random Forest Classifier (RFC)
- Naive Bayes (NB)
- Ada Boost (AB)
- Extra Trees Classifier (ETC)
- Logistic Regression (LR)
- K Nearest Neighbour (KNN)
- Multi-Layer Perceptron (MLP)
- Decision Tree (DT)

Table 1: Nepali WordPiece Tokenization

Sentence	Tokenized text
हिमालमा चिसो हुन्छ (It is cold in the mountains)	[“हिमाल”,”##मा”,”चिसो”,”हुन्छ ”]

Due to the small size of the datasets, machine learning-based algorithms have been used for text classification. The dataset developed for sentiment analysis had been split with an 80-20 rule to generate training and testing datasets. WordPiece Tokenizer had been used for the tokenization of Nepali sentences before feature engineering. An example of WordPiece Tokenizer is given below.

The evaluation metrics shown in Table 2 were obtained while applying transfer learning on the Distil BERT base Nepali model, NepaliBERT model, NepBERTa model, and nepaliBERT model:

5 DISCUSSION AND ANALYSIS

From the research of the comparison of transfer learning applied to the sentiment analysis data on four open source, Nepali pretrained large language models, it was analyzed that the NepBERTa model yielded the best results in terms of testing evaluation metrics. These models can also be used for other downstream NLP tasks such as

Table 2: Evaluation Metrics obtained from different pretrained Nepali language models

Algorithm	NepaliDistilBERT model			NepaliBERT model			NepBERTa Model			NepaliBERT model(ours)		
	Precision	Recall	F-Score	Precision	Recall	Fscore	Precision	Recall	F-Score	Precision	Recall	F-Score
SVC	0.87	0.87	0.87	0.82	0.82	0.82	**0.87**	**0.87**	**0.87**	0.86	0.86	0.86
RFC	0.79	0.76	0.75	0.74	0.65	0.58	**0.79**	**0.79**	**0.79**	0.77	0.74	0.71
NB	0.81	0.80	0.81	0.74	0.74	0.73	**0.81**	**0.80**	**0.81**	0.81	0.80	0.80
AB	0.83	0.83	0.83	0.79	0.79	0.79	**0.84**	**0.84**	**0.84**	0.83	0.80	0.80
ETC	0.87	0.87	0.87	0.83	0.82	0.82	**0.87**	**0.87**	**0.87**	0.86	0.86	0.86
LR	0.85	0.85	0.85	0.82	0.82	0.82	**0.85**	**0.85**	**0.85**	0.84	0.84	0.84
KNN	0.83	0.83	0.83	0.77	0.77	0.77	**0.83**	**0.83**	**0.83**	0.81	0.81	0.81
MLP	**0.88**	**0.88**	**0.88**	**0.85**	**0.85**	**0.85**	**0.88**	**0.88**	**0.88**	**0.88**	**0.88**	**0.88**
DT	0.74	0.74	0.73	0.67	0.68	0.67	**0.74**	**0.74**	**0.74**	0.73	0.73	0.73

Table 3: Example of Inference

Sentence	Sentiment Polarity
गणेशमान सिंह नेपालीको असल राजनेता हुन् (Ganeshman Singh is a good politician of Nepal)	1
यो मान्छे त हेर्दै चोर जस्तो छ (This man looks like a thief)	0

Question Answering, and Named Entity Recognition (NER) similarly. The embeddings of each Nepali sentence are first calculated using the approach discussed for sentence embedding calculation above and these embeddings can be used as a feature for further downstream tasks.

The NepBERTa pre-trained language model gave the best results among the open-source pre-trained language models whereas the Multi-Layer Perceptron (MLP) algorithm gave the best results among the machine learning algorithms used for the classification of the sentiments in the Nepali language.

The models that have been developed using the transfer learning approach are highly accurate and very low in size so that they can be used at the production level. The inference time of the model is very low making the model efficient in production level. An example of the model generating sentiment polarity for two sentences is shown below in Table 3.

6 CONCLUSION

The research investigated the applications of transfer learning from open-source Nepali pre-trained large language models (LLMs) for sentiment analysis. The results obtained successfully demonstrates that leveraging pre-trained representations improves performance on this downstream NLP task. We:

- Extracted effective sentence embedding representations from pre-trained LLMs.
- Identified the best-performing open-source Nepali LLM based on sentiment analysis evaluation metrics.
- Released the models, sentiment analysis data, and experiment files readily accessible through a public Github repository.

However, it's crucial to acknowledge that the efficacy of sentiment analysis models, regardless of language, can vary depending on the data source and domain specificity. While this research performs well on the YouTube sentiment data, it might not achieve optimal results on other domains like e-commerce reviews. This finding highlights the importance of domain-specific fine-tuning for achieving optimal performance.

7 FUTURE WORK

Building upon this research, several exciting avenues for future exploration exist:

- Domain-specific Fine-tuning: Investigate and develop techniques for effectively fine-tuning pre-trained Nepali LLMs to specific domains like e-commerce, news, or social media. This could involve creating domain-specific datasets and implementing targeted fine-tuning methodologies.
- Contextual Understanding: Analyze and address the challenges of accurately capturing context-dependent sentiment in Nepali text. This might involve exploring models that consider sentence structure, dialogue flow, or speaker/writer intent to further refine sentiment analysis.
- Multilingual Collaboration: Explore the potential of incorporating knowledge from other languages into Nepali sentiment analysis. This could involve multilingual transfer

learning techniques or building joint embedding models for languages with similar cultural contexts.

- Ethical Considerations: Develop and implement ethical guidelines for responsible development and application of sentiment analysis models in the Nepali language. This includes addressing issues like bias, privacy, and potential misuse of sentiment analysis technologies.

By expanding on these and other future research directions, researchers can deepen the understanding of Nepali sentiment analysis and contribute to the development of robust and ethically responsible NLP applications for the Nepali language community.

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