Sentiment Analysis in Low-Resource Languages: A Comprehensive Review on Current Methodologies

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Abstract
Low-resource languages are languages that have limited resources and data available for natural language processing tasks, such as sentiment analysis. This review aims to provide an overview of the current state-of-the-art methodologies of sentiment analysis on low-resource languages, with a focus on languages like Hausa and other under-resourced languages. The review first discusses the importance of sentiment analysis on low-resource languages, highlighting the cultural and linguistic significance of these languages. It analyzed previous works on sentiment analysis techniques, including traditional machine learning approaches and deep learning methods. The review also covers the datasets and resources currently available for sentiment analysis on low-resource languages, highlighting their limitations and potential for improvement. Additionally, it also discusses the challenges faced in low-resource languages like lack of annotated data, lack of linguistic resources, and lack of computational resources. papers related to low-resource languages were examined. These papers were selected based on a filtering process, considering the relevance of the topic to the research. Finally, the review concludes by discussing the future directions and potential solutions for sentiment analysis on low-resource languages, including the use of unsupervised methods, and the development of more comprehensive datasets and resources. Overall, this review provides a comprehensive overview of the current state of sentiment analysis on low-resource languages and highlights the challenges and opportunities for future research in this field.

Keywords: social network, low-resource language, natural language processing, sentiment analysis, machine learning, and deep learning.

INTRODUCTION

Researchers in natural language processing (NLP), especially in the field of sentiment analysis, have found it hard to work with low-resource languages (LRLs). Many of the tools that are used to train and test sentiment analysis models, like annotated datasets, lexicons, and models that have already been trained, are not available for these languages. Even though interest in sentiment analysis for different languages, including LRLs, is growing, there is still not enough research on the topic, especially on how to adapt and build models for these languages. In light of this, the goal of this paper is to give a full review of the current state of sentiment analysis in LRLs, focusing on the challenges, limitations, and future directions of this research area.

Traditionally, the detection of hate speech on social networks is based on high-resource languages such as English, and models for these languages are often used. But this method has problems when it comes to finding hate speech in low-resource languages (LRLs) like Hausa. Because there aren't enough datasets and other problems with LRLs, there isn't much research and modeling for these languages. This gives researchers a chance to come up with ways to find hate speech in local languages that work well. In the past, cyberbullying on social media platforms has been stopped in a number of ways, such as by screening posts that break the platform's rules. They called the method "sentiment analysis." It uses natural language processing (NLP) to pull opinions out of text, figure out what they mean, and put them into positive, negative, or neutral categories [1].

Schmidt et al. [2] suggest that there is a strong correlation between hate speech and sentiment analysis, where negative sentiment is often associated with hate speech. So, many ways to find hate speech use sentiment analysis as an additional way to classify it. Sentiment analysis is an active area of research with many growing subtopics of interest. Even though extensive work has been done in this field with high-resource languages, there are still numerous challenges that need to be tackled, particularly with low-resource languages (LRLs). These challenges include making new models to do similar tasks in LRLs, improving the performance of existing models, proposing more advanced models using new technologies, reducing processing time, and adapting techniques made for specific languages and domains to others. Hence, this research will provide a thorough review of LRLs such as Hausa, Yoruba, Ibo, Spanish, and Arabic, among others.

NATURAL LANGUAGE PREPROCESSING

Natural Language Processing (NLP) is a branch of computational linguistics that deals with creating computational models and techniques to solve practical issues in understanding human languages. These solutions are utilized to construct useful software. NLP can be broken down into two main parts: core areas and applications. However, it can be hard to tell them apart. The core areas focus on fundamental issues such as language modeling, which involves quantifying the associations between naturally occurring words; morphological processing, which handles the segmentation of meaningful components of words and identifies the parts of speech of words; syntactic processing, which creates sentence diagrams as a precursor to semantic processing; and semantic processing, which tries to extract the meaning of words, phrases, and higher-level components in text [3]. Khurana et al. [4]The application areas include things like finding useful information, translating text between languages, summarizing written works, automatically answering questions, and classifying and clustering documents. Often, to solve practical problems, you need to solve one or more of the core issues.

At the moment, most of NLP is based on data and uses statistical and probabilistic calculations along with machine learning. Hidden Markov models, support vector machines, decision trees, random forests, Naive Bayes, k-nearest neighbors, and conditional random fields were popular machine learning algorithms in the past [3].

In the past few years, there has been a big change in NLP, with neural models replacing or adding to traditional machine-learning methods. These neural models include convolutional neural networks (CNN), recursive neural networks, recurrent neural networks, long short-term memory networks, residual connections, and dropout, among others [3].

Also, pre-trained models such as BERT are leveraged. BERT (Bi-directional Encoder Representations from Transformers) is a pre-trained model that uses unlabeled text from sources like the Book Corpus and English Wikipedia[4].

Machine learning algorithms in sentiment analysis.

According to Wang et al. [5] the field of research that allows computers to learn on their own without explicit programming was defined as "machine learning" in 1959. Even though this description isn't very clear, it does show an important part of machine learning: it doesn't follow "rules" that have already been programmed. In general, machine learning is an automated process that lets machines look at a lot of data, find patterns, and learn from the data to help with predictions and making decisions.

Furthermore, Mahwsh [6] Machine learning is divided into three categories: supervised, unsupervised, and reinforcement learning. "Supervised learning is a machine learning task that learns to map inputs to outputs based on labeled examples." It involves deriving a function from a set of labeled training instances, where the input dataset is divided into two parts: training and test sets. The training set includes an output variable that needs to be predicted or categorized. The supervised machine learning algorithms learn patterns from the training data and use them to predict or classify the test data. This process requires external intervention. Some of the supervised machine learning algorithms are Decision Tree, Naive Bayes, Support Vector Machine, gradient boosting, and machine and logistic regression. These are the most commonly used machine learning models in sentiment analysis. Even though their results depend on the dataset, some of these models, like logistic regression and Naive Bayes, are often considered good starting points for sentiment analysis tasks.

Deep learning algorithms in sentiment analysis

Alzubaidi et al. [7] say that DL is based on traditional neural networks, but it does a lot better than them. DL also uses both transformations and graph technology to build models of learning with more than one layer. Recently developed deep learning (DL) algorithms have demonstrated outstanding performance in a wide range of applications, including audio and speech processing, visual data processing, and natural language processing (NLP), among others.

Deep learning uses a multi-layer approach to the hidden layers of neural networks. Traditional machine learning methods rely on manually selecting or extracting features. Deep learning models, on the other hand, train and extract features automatically, which makes them more accurate and better at what they do. Additionally, the hyper parameters of classifier models are also automatically adjusted. Some deep learning algorithms include CNN and MLP [8].

Pre-trained model in sentiment analysis

The most popular pre-trained model used in sentiment analysis is the BERT, which is a model that uses unlabeled text from sources such as the Book Corpus and English Wikipedia [4]. This model can be tweaked to capture context for a wide range of NLP applications, such as answering questions, analyzing sentiment, categorizing text, embedding phrases, and figuring out what a text means when it's not clear what it means. Earlier language-based models examined the text in either one direction, which was used for sentence generation by predicting the next word, whereas the BERT model examines the text in both directions simultaneously for better language understanding. In contrast to context-free models like word2vec and GloVe, BERT gives each word in the text an embedded context.

Also, Khurana et al. [4]say that one of BERT's weaknesses is that it can't handle long sequences of text. Since BERT can only look at up to 512 tokens, a long string of text must be broken up into many smaller strings of 512 tokens each.

METHODOLOGY

The goal of this paper is to take an in-depth look, and critically analyze the algorithms used for low-resource languages. A thorough review of the literature will be conducted, by identifying reputable scholarly databases such as IEEExplore, Springerlink, ACM digital library and ScienceDirect, among others. The search string "sentiment analysis AND low resources language OR languages" will be used in all the databases. Articles will be selected based on the inclusion and exclusion criteria to choose papers for this review. Figure 1 describes the framework of the methodology that will be employed in this study.

Inclusion criteria:

The inclusion criteria for articles to be used in this study is as follows:

1- The paper must mentioned sentiment analysis in its title and abstract

2- The paper must be written in English

3- The paper must be found in one of the databases identified above

Exclusion criteria

1- The paper must have at least 5 citations

2- The paper must have at least two authors

3- The paper must be a journal article or conference proceedings.

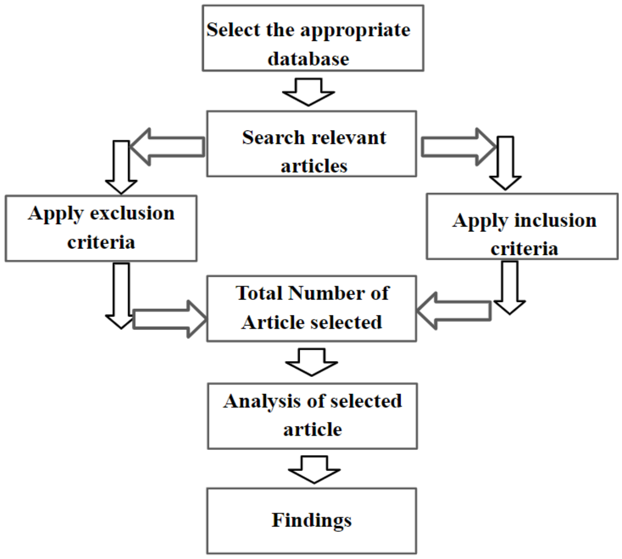

Figure 1: A framework of the Methodology

RESULT

This section presents the discussion of the results, and findings of the study. therefore the section is divided into two parts; section A, and section B.

Section A

Muhammad et al. [9] addressed the problem of sentiment analysis in low-resource languages by annotating about 30,000 tweets in Hausa, Igbo, Yoruba, and Nigerian Pidgin, as well as establishing a sentiment lexicon in three languages (Hausa, Igbo, and Yoruba). After telling the three annotators marked words that showed a negative or positive attitude, the simple majority vote was used. They employed AfriBERTa-large, mBERT-base, XLM-R-base, mDeBERTaV3-base, and RemBERT as pre-trained models. According to the data, the majority classifier performs between 16-45% for all languages when using the weighted F1-score and 33-56% when using the micro F1-score. PLMs, on the other hand, have at least a 70% F1-score, demonstrating their utility for sentiment analysis.

Furthermore, Rakhmanov et al. [10] add to NLP. The authors used classification models like random forest (RF), support vector machines (SVM), multilayer perceptrons (MLP), long-short-term memory (LSTM), bidirectional LSTM (bi-LSTM), and natural language processing (NLP) models to analyze the sentiment of the dataset. They first compared the Hausa model's performance in the dataset to English, where they construct and test systems with EN-HESAC. The systems' accuracies of more than 94.4% show that the models learn about language rather than just repeating sentiment labels from training data. They compared the performance of a Hausa sentiment analysis model to English and found that the Hausa model achieved 94.4% accuracy. They also tested cross-language systems and found that they worked as well as English. They also looked at monolingual systems and found that LSTM with stemming was the most accurate, with a 97.4% accuracy rate.

Plaza et al. [11] suggested a sentiment analysis-based machine learning-based hate speech detection approach for minimizing hate speech on social media. The scientists employed a transformer-based model to assist in filtering or blocking inappropriate information on the internet. A detailed knowledge transfer analysis from SA and how well the proposed model works show that polarity and emotion classification tasks help the MTL model recognize HS by using emotional information. The effects of affective knowledge and HS are related, which opens the door to new methods for constructing NLP systems in other disciplines where polarity and emotion may be important. The model has flaws since multitasking uses different corpora for classification, which raises the computational cost.

Sani et al. [18] engaged in a project to solve the issue of Hausa sentiment on the BBC Hausa Twitter handle. To improve categorization results, the authors employ both machine learning and lexicon-based techniques. The proposed model was employed on the Hausa data set generated from the BBC account on Twitter. With the count vectorizer and TF-IDF method, we used the multinomial naive Bayes (MNB) and logistic regression (LR) algorithms to divide the text into two groups, positive and negative. With the model's assistance, a considerable improvement in text categorization performance was achieved. Except for the time required to train the data and the memory usage during data classification, the result clearly reveals that the logistics regression algorithm outperforms the multinomial Naive Bayes classification algorithm.

Abubakar et al. [12] also showed a model that will make it easier to figure out how people feel about tweets in English and Hausa. Using an Enhanced Feature Acquisition Method, the research proposes multilingual sentiment analysis of English and Hausa tweets (EFAM), SVM, Naive Bayes, and MaxEnt. The method integrates two newly developed Hausa features (Hausa Lexical Feature and Hausa Sentiment Intensifiers) with an English feature to measure classification performance and construct a more accurate sentiment classification procedure. Several tests with various classifiers in both monolingual and multilingual datasets were conducted to evaluate the strategy. The experimental findings demonstrate the approach's effectiveness in improving feature integration for multilingual sentiment analysis. Similarly, they build machine learning classifiers with an average precision of more than 65% by combining information from multiple languages.

The research of Oriola et al. [13] Focuses on Twitter as a social network; they conduct the research with domain-specific English in detecting offensive and hate speech. Annotators who spoke more than one language worked on the corpus because the tweets used words from South African languages. They use machine learning algorithms such as logistic regression, support vector machines, gradients, and random forests to better classify South African tweets as free speech, hate speech, or offensive speech. A multi-tiered meta-learning model (support vector machine, random forest, and gradient) has true positive rates of 0.887 and 0.858 for finding offensive and hate speech, with an overall accuracy of 0.671. Hyper-parameter optimization, ensemble learning, and multi-tier meta-learning were employed to improve the machine learning model.

López-Chau et al. [14] conducted another study on sentiment analysis of Twitter data using machine learning techniques. The goal of this study is to produce and analyze data sets based on topics trending on Twitter that came from Mexican residents who interacted during the September 19, 2017 earthquake. Based on Ekman's six emotional models, the authors proposed that three classifiers be created to assess the emotions of tweets based on the topic using sentiment analysis and supervised learning. Neural networks, logistic regression, decision trees, Naive Bayes, and support vector machines are examples of machine learning approaches. Where the last two are the most accurate at predicting emotions.

Many training models, including MUSE + CNN-GRU, BERT, LASER + LR, mBert, and translator, were used as a solution. The authors investigate two scenarios for running the models: monolingual and multilingual. MUSE + CNN-GRU, BERT, LASER + LR, translator, and mBert models all run on nine distinct languages for the monolingual scenario, including Arabic, German, Indonesian, Italian, Polish, Portuguese, Spanish, French, and English. The model was trained on 16, 32, 64, 128, and 256 complete training sizes with varying levels of accuracy. Many training models, including MUSE + CNN-GRU, BERT, LASER + LR, mBert, and translator, were used as a solution. The authors explore running the models in two separate scenarios: monolingual and multilingual. For the monolingual situation, the MUSE + CNN-GRU, BERT, LASER + LR, translator, and mBert models all run on nine distinct languages, including Arabic, German, Indonesian, Italian, Polish, Portuguese, Spanish, French, and English. The model was trained on 16, 32, 64, 128, 256, and complete data training sizes, and various accuracy values were obtained. Later, they deem LASER + LR and mBERT to be the most significant for the analysis. Hence, LASER + LR and mBERT were the models utilized for the multilingual scenario. Finally, their data reveal that, in low-resource languages, LASER + LR beats BERT, whereas in high-resource languages, BERT outperforms LASER + LR [15]

Ruz et al. [16] on the other hand, conducted research on the sentiment analysis of Twitter data during critical events employing Bayesian network classifiers. They recommended creating a model with five classifiers to help with sentiment analysis. The natural catastrophes that occurred in Chile in 2010 and in the 2017 Referendum on Catalan Independence the authors used two Twitter datasets from two important events: the 2010 Chilean earthquake and the 2017 Catalan independence referendum, and tested five classifiers (one of which was a variation of the TAN model). They conclude that SVM and RF behave similarly in English and Spanish. In terms of model accuracy, SVM outperformed RF in dataset 1 and TAN outperformed SVM in dataset 2, but when there was enough data to support the tree structure, the Bayesian network classifier TAN surpassed SVM.

Also, Dang et al. [17] made a model for using hybrid techniques in sentiment analysis. This model has been shown to be a possible way to reduce mistakes in sentiment analysis on training data that is getting more complicated. Long-term memory (LSTM) networks, convolutional neural networks (CNN), and support vector machines are the hybrid deep sentiment analysis learning models (SVM). The research technique focused on three primary components: the process of creating feature vectors, the data to be used, and the development of hybrid methods for a suitable sentiment analysis solution. Long-short-term memory (LSTM) networks, convolutional neural networks (CNN), and support vector machines (SVM) were created and used on eight tweets. Datasets from different fields were also looked at to predict and identify the polarity of the text's sentiment. Using two-word embedding approaches, Word2Vec and BERT, the performance of combining SVM, CNN, and LSTM was evaluated. They tested four hybrid models that were made at random and compared them to single models. Their results show that combining deep learning models with the SVM technique gives better results for sentiment analysis than using a single model. In the majority of the datasets evaluated, hybrid models that use SVM outperform those that do not. However, the computational time is significantly longer.

The summary of the methodologies can be best described in the bar chart below, which shows the popularity of a methodology based on the number of publications.

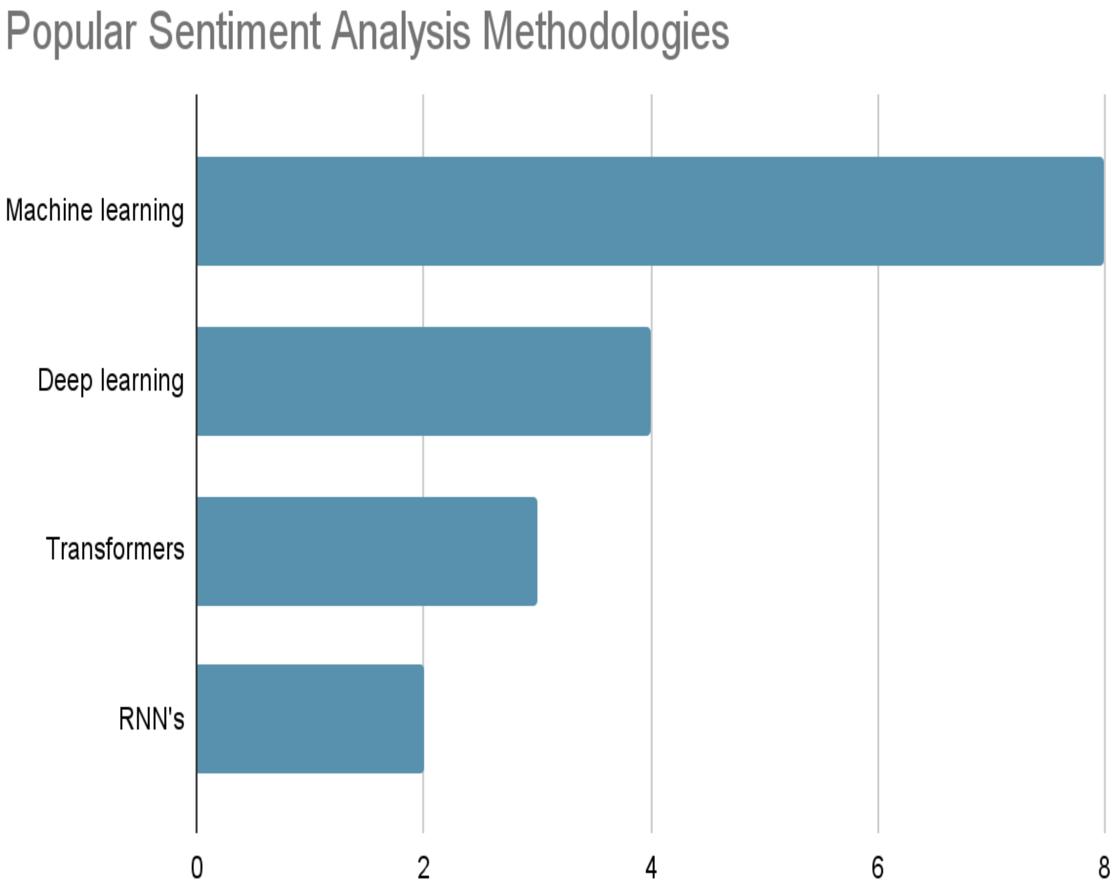

Figure 2: A bar chart depicts the popularity of various methodologies

Section B

The summary of the related work can be viewed in the below table:

Table I: Summary of related works

S/N	Paper/Article	authors/year	The problem to solve in the paper	The solution to the problem	How is the solution achieved?	Comment
1.	NaijaSenti: A Nigerian Twitter Sentiment Corpus for Multilingual Sentiment Analysis	Muhammad, S. H.et al.(2022)	The research aim was to generate a large dataset in low-source languages like Hausa, Igbo, Pidgin, and Yoruba.	They propose labeling methods, text collection, filtering, and processing to create datasets for these low-resource languages, using BERT.	As a result of their work, they were able to mark up about 30,000 tweets in Hausa, Igbo, Yoruba, and Nigerian Pidgin and create a sentiment lexicon in Hausa, Igbo, and Yoruba. PLMs have an F1-score of at least 70%, proving their utility for sentiment analysis.	The study uses Twitter as the main source of data for low-resource languages, but it would be beneficial to also explore other platforms like Facebook.
2.	Sentiment Analysis for Hausa: Classifying Students' Comments	Rakhmanov, O et al.(2022)	To investigate student sentiment on course evaluation	The authors conducted sentiment analysis on a dataset using various classification models such as RF, SVM, MLP, LSTM, bi-LSTM, and NLP models.	They compared the performance of a Hausa sentiment analysis model to English, and found that the Hausa model achieved 94.4% accuracy. They also tested cross-lingual systems and found that they could achieve similar performance to English. They also evaluated monolingual systems and found that LSTM with stemming had the highest accuracy at 97.4%.	Their work is solely for students' feedback on courses they took.

3.	A Multi-Task Learning Approach to Hate Speech Detection Leveraging Sentiment Analysis	Plaza-Del-Arco et al.(2021)	to detect hate speech made on social media posts (Twitter) in Spanish.	The authors came up with a way to find hate speech using multi-task learning and sentiment analysis to build a transformer-based model that can filter or block inappropriate information on the internet.	The performance of the proposed model shows that polarity classification tasks and emotion classification tasks help the MTL model classify HS well by using emotional information. The linked impacts of affective knowledge and HS open the door to new approaches to developing NLP systems in other fields.	The problems with the model are caused by the fact that multitasking uses other corpora to classify, which raises the cost of computing.
4.	Sentiment Analysis of Hausa Language Tweet Using Machine Learning Approach	Sani, M., et al.,(2022)	The project's goal is to address the problem of Hausa sentiment on the BBC Hausa Twitter account.	To improve categorization results, the authors employ both machine learning and lexicon-based techniques.	The proposed model was employed on the Hausa data set generated from the BBC account, on Twitter. The multinomial naive Bayes (MNB) and logistic regression (LR) algorithms were used to classify the text. With the model's assistance, a considerable improvement in text categorization performance was achieved.	The study focuses on a single Twitter handle, the BBC Hausa, as the source for a dataset in the Hausa language
5.	An Enhanced Feature Acquisition for Sentiment Analysis of English and Hausa tweets.	Abubakar A. I et al.(2021)	To present a model that will improve sentiment analysis of tweets in English and Hausa.	Enhanced Feature Acquisition Method (EFAM) which are Naïve Bayes, SVM, MaxEnt	A bilingual sentiment analysis of English and Hausa tweets is proposed in the study. They use information from different languages to create machine-learning classifiers with an average precision of more than 65%. Several tests with various classifiers were run on both monolingual and multilingual	Despite the authors' efforts to refine the sentiment analysis model, there is still room to increase the model's performance accuracy.

					datasets. with SVM has a high accuracy of 71% on the Hausa dataset.	
6.	Evaluating Machine Learning Techniques for Detecting Offensive and Hate Speech in South African Tweets	Oriola, O et al.(2020)	to detect offensive and hate speech in South African tweets, and compare similarities between offensive, hate, and free speech in the English corpus.	They proposed the use of different machine learning techniques to detect offensive and hate speech in an English corpus of South African tweets. Such as SVM, random forest, and gradient.	Researchers used machine learning algorithms to improve the classification of South African tweets as free speech, hate speech, or offensive speech. They used methods like logistic regression, support vector machines, gradients, and random forests. They achieved high true positive rates and an overall accuracy of 0.671, and improved the model with techniques like hyper-parameter optimization, ensemble learning, and multi-tier meta-learning.	The study only takes into account tweets from South Africa.
7.	Sentiment Analysis of Twitter Data Through Machine Learning Techniques	López-Chau et al (2020)	This research aims to study Twitter data from Mexican citizens during the 2017 earthquake.	Three classifiers were built to determine emotions in tweets using sentiment analysis and supervised learning based on Ekman's six emotional models: SVM, logistic regression, naive bayes, decision trees, and the neutral network.	The most frequently predicted emotions were happiness, anger, and sadness. Researchers found that 6.5% of predicted tweets were irrelevant. The range of emotions goes from three (negative, neutral, and positive) to six. This is done so that researchers can learn more about how people use social media platforms. There were very few emotions of	Validation of the sentiment analysis method with different emotions and datasets, and improvement of accuracy with AI techniques are needed.

					surprise (3.9%), disgust (4.2%), and fear (0.7%) in all the analyzed data because much of the data were collected after the earthquake. Ambiguous tweets represented the 6.5% of data	
8.	Deep Learning Models for Multilingual Hate Speech Detection	Aluru, S. S., et al.(2022)	Use deep learning for sentiment analysis in low-resource languages on Twitter data.	Different training models were used as the solution, such as MUSE + CNN-GRU, BERT, LASER + LR, mBert, and translator.	The authors use different training sizes to test models on multiple languages and discover that LASER + LR and mBERT perform well in low- and high-resource languages, respectively.	Hausa is not included among the nine languages considered by the authors.
9.	Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers	Ruz et al. (2020)	The goal is to analyze sentiment during critical events using a deep learning model.	They came up with a five-classifier model for analyzing how people felt about natural disasters from 2010 to 2017.	The authors tested five classifiers on two datasets from two events and found SVM and RF performed similarly in English and Spanish, and TAN outperformed SVM when there was enough data to support the tree structure.	Further research is needed to combine machine learning with traditional social science techniques for emergency management.
11.	Hybrid Deep Learning Models for Sentiment Analysis	Dang et al.(2021)	The aim is to see if hybrid models can outperform single models with different domains and types of data in different fields.	The authors proposed using hybrid techniques of LSTM, CNN, and SVM for reducing sentiment errors on complex training data.	The research shows that combining deep learning models with support vector machines (SVM) yields better results than using individual models for performing sentiment	sentiment analysis on hybrid data sets and numerous hybrid contexts in order to gain greater insight into a given topic, such as business, marketing, or medicine.

					analysis. In most of the tested datasets, the reliability of hybrid models using SVM is higher than that of those not using it. The computational time is much longer for the ones with SVM.	

FUTURE DIRECTION

At the end of this review, it is discovered that more efforts need to be made to provide better models that work on low-resource languages as well as they work on high resource ones. It has also been discovered that the field of NLP is rapidly expanding, as evidenced by an increase in the number of publications each year. In conclusion, the following future directions were identified: Many studies in low-resource languages were challenged due to the scarcity of annotated datasets and lexicons. This is because researchers often focus on one source of data, such as Twitter, because it is easy to use via API authentication, while overlooking other social networks like Facebook, where many people engage and participate in their native language.

Secondly, almost all of the research works only address one type of data context, such as text, images, or audio. With this, there is a need to make multimodal data set models that can handle multiple modalities, since sentiment analysis in low-resource languages also involves handling multimodal data like text, images, and audio.

More work needs to be done regarding the pre-processing steps of low-resource languages, such as word embedding and stemming, as adapting pre-trained models to low-resource languages is challenging.
According to this analysis, the majority of NLP research in low-resource languages focuses on sentiment analysis. So, in order to broaden the scope of NLP in low-resource languages, researchers need to focus on some recently developed topics, like idiomatic expressions in low resource languages.

CONCLUSION

In conclusion, sentiment analysis in low-resource languages is a challenging task because training models from scratch is very expensive, and adopting pre-trained models requires significant changes as the models were not originally trained on LRLs. Other problems include a lack of annotated datasets and lexicons, dealing with different languages and dialects, handling multimodal data, judging how well models work, and making them work better. Even with these problems, there is a growing interest in sentiment analysis for low-resource languages and a need for more research in the area. In the end, this paper gave a full review of the current state-of-the-art methods for sentiment analysis in low-resource languages, focusing on the challenges, limitations, and future directions of the research area. It shows that NLP is an active field of research that is growing exponentially. It is hoped that this review will provide valuable information for researchers working in this field and will encourage further research in sentiment analysis for low-resource languages.

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