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A NOVEL TRANSFER DEEP LEARNING FRAMEWORK WITH CROSS-LINGUAL EMBEDDINGS FOR HIGH-RESOURCE AND LOW RESOURCE LANGUAGES FOR SENTIMENT ANALYSIS

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SUMMARY

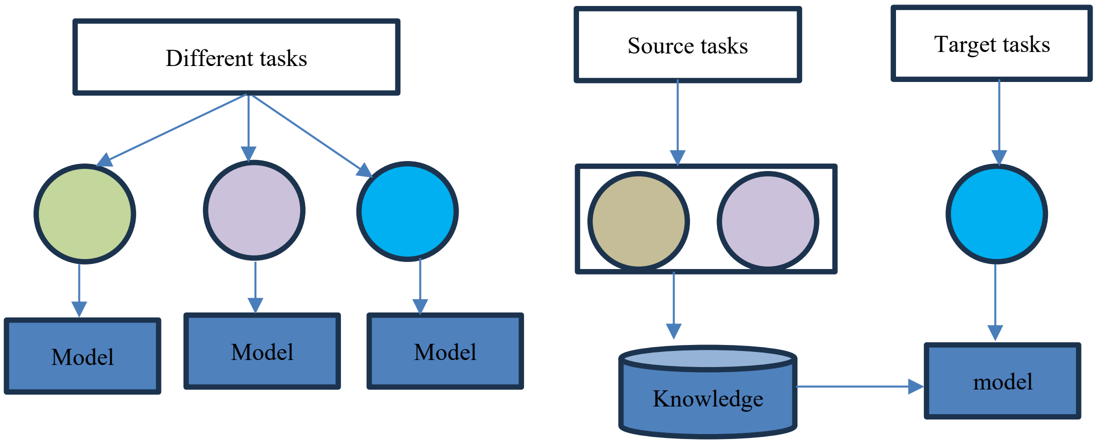
Sentiment analysis (SA) is important in comprehending the opinions and online discussions of people in different languages, particularly in high-resource and low-resource languages. In the present paper, a new model of transfer deep learning is presented, which incorporates cross-lingual embeddings in an attempt to boost sentiment analysis in both high and low-resource languages. HRLs get access to a vast number of linguistic resources and datasets, and LRLs have to grapple with the lack of labeled data, which makes the classic models of machine learning unproductive. The suggested framework uses transfer learning (TL) to mitigate these difficulties so that models trained on HRLs could be applied to LRLs, which would help in the problem of data scarcity. The model is a hybrid deep learning model, which uses both pre-trained models and cross-lingual embeddings, that can enhance the sentiment classification performance of both HRLs and LRLs. The comprehensive experiments of the multilingual data, as well as Twitter data, testify to the fact that the offered method is more effective than the traditional models. As an example, the proposed method has an accuracy of 96.42%, which is higher than Bi-LSTM and Bi-GRU with 91.45% and 88.57% accuracy, respectively. This performance depicts the efficiency of the suggested methodology in sentiment analysis in under-resourced languages. The findings show that the transfer learning can be used to substantially expand multilingual sentiment analysis through the use of transfer learning. These models can be further optimized to produce regionally specific languages in future studies and make them more scalable.

Key words: *transfer learning, deep learning, multilingual sentiment analysis, cross-lingual embeddings, low-resource languages, high-resource languages, sentiment classification.*

INTRODUCTION

Due to their limited availability, inaccessibility, high cost, and difficulty in compiling, data sets are becoming increasingly out of reach for most people in today's society. The majority of individuals thus discovered more efficient methods of data gathering, one of which is the transfer of knowledge between tasks [1]. This idea has given rise to Transfer Learning (TL), which aims to enhance data collection and learn ML from pre-introduced data. The majority of ML algorithms focus on making predictions, which has always been useful for dealing with jobs independently [2]. In contrast, TL does the exact opposite; it takes input from several sources and applies it to a specific job in order to discover a solution and maybe a better one.

The goal of task-level reasoning (TL) is to enhance comprehension of the present activity by drawing connections to related tasks completed at various times but via the same source domain. You can see the results of using the TL approach to ML in Figure 1. It improves learning by making connections between unrelated activities and the one at hand, which in turn leads to more efficient, well-thought-out solutions. Although TL aims to facilitate effective learning and communication between source and target tasks, the efficacy of this approach is questionable [3]. Another scenario where TL really shines is when the target training data is limited. When used strategically, TL can be useful not just within the context of the job at hand, but also in relation to and even beyond it [4][5]. Nevertheless, there are instances when the source and destination tasks do not have a compatible relationship. A negative transfer occurs when the user moves the training and testing samples from one task to another, and vice versa; this lowers the performance of the target task.



a) traditional machine learning

b) transfer learning

Figure 1. Machine learning (VS) transfer learning [Source 5]

An important part of natural language processing is sentiment analysis, which entails identifying the underlying attitude or emotional tone of a document [6]. Marketing, customer service, and gauging public sentiment on social issues are just a few of the many areas where it is extremely valuable [7]. Businesses can gain significant insights into client feedback and make informed decisions with the use of sentiment analysis, which automatically classifies text as positive, negative, or neutral [8]. Recent sentiment analysis studies have shifted their attention from well-resourced languages to less well-resourced ones, such as African languages, and have used transformer-based natural language processing models to address these challenges [9][10][11]. Nevertheless, these models' interpretability and explainability have not been investigated. Since these languages frequently do not have enough labelled data and resources, they pose special difficulties for current sentiment analysis models and are hence considered low-resourced. Further complicating matters for existing models is the widespread perception of multilingual communities' usage of Twitter (now X) and other social media platforms as normal practice [12]. A number of ways have been suggested by researchers to tackle these challenges; they include machine learning and DNN techniques [13], as well as transfer learning & multidisciplinary and cross-lingual approaches [12]. Recently, multilingual pre-trained language models (PLMs) and sentiment datasets for languages with limited resources have emerged. These disadvantaged languages benefit from these models' fine-tuning for particular natural language processing tasks.

A flood of material reflecting people's views appears on newsfeeds due to the rapidity with which people may express themselves on social media [14]. Their feelings and thoughts can be directly captured by analyzing these newsfeeds. Opinion mining and sentiment analysis are two terms for the same thing: the use of text analysis or computational linguistic approaches in Natural Language Processing (NLP) to find, extract, and classify particular data from unstructured texts [15]. SA entails sorting linguistic content based on its polarity into positive, negative, or neutral categories [16][17][18]. Since LRL processing increases the number of languages that can be analyzed, it has a significant impact on SA. This opens up the possibility of using SA for languages with low digital resources, which helps to increase the cultural diversity and inclusivity of sentiment analysis. Organizations can enhance their worldwide market understanding by gaining insights into sentiment patterns, customer preferences, and brand image in underserved regions and languages. There are far-reaching consequences for SA in the globally interdependent world due to LRL processing, which enables cross-cultural analysis, aids humanitarian operations in crisis responses, and helps preserve endangered languages.

Because LRLs are often spoken by marginalized or underprivileged communities, they pose special difficulties for natural language processing researchers. In contrast to high-resource languages like English, which have access to a plethora of digital resources, including pre-trained models and huge, labeled datasets, these languages do not. Despite the limited resources, there are numerous compelling reasons why tackling LRL processing is crucial. Limited accessibility and use of NLP technology for LRLs is the primary challenge that this research project seeks to address. Inadequate linguistic resources, a lack of labeled datasets, and unproven language technologies are just a few of the many obstacles this encounter. Consequently, fresh methods are required immediately to increase the availability, influence, and efficacy of LRL processing.

Research into text categorization using several features is still ongoing and promising [19]. To make this field of study better all the time, SA and opinion mining use DL, ML, and rule-based systems. The development of sophisticated language models that can draw on prior knowledge and tailor it to specific tasks has led to enhanced performance with reduced computational resource consumption [20]. Language models that rely on deep neural networks (DNNs) are particularly intriguing because of their remarkable sentiment classification capabilities, which they acquire automatically from databases by learning crucial features. The results, however, are quite language and, more specifically, database accessibility dependent, since they were utilized to train the model first. Languages other than Chinese and English are usually considered LRLs, and this condition is usually reserved for those two languages alone. It is common practice to automatically measure the hyperparameters of classifier models as well.

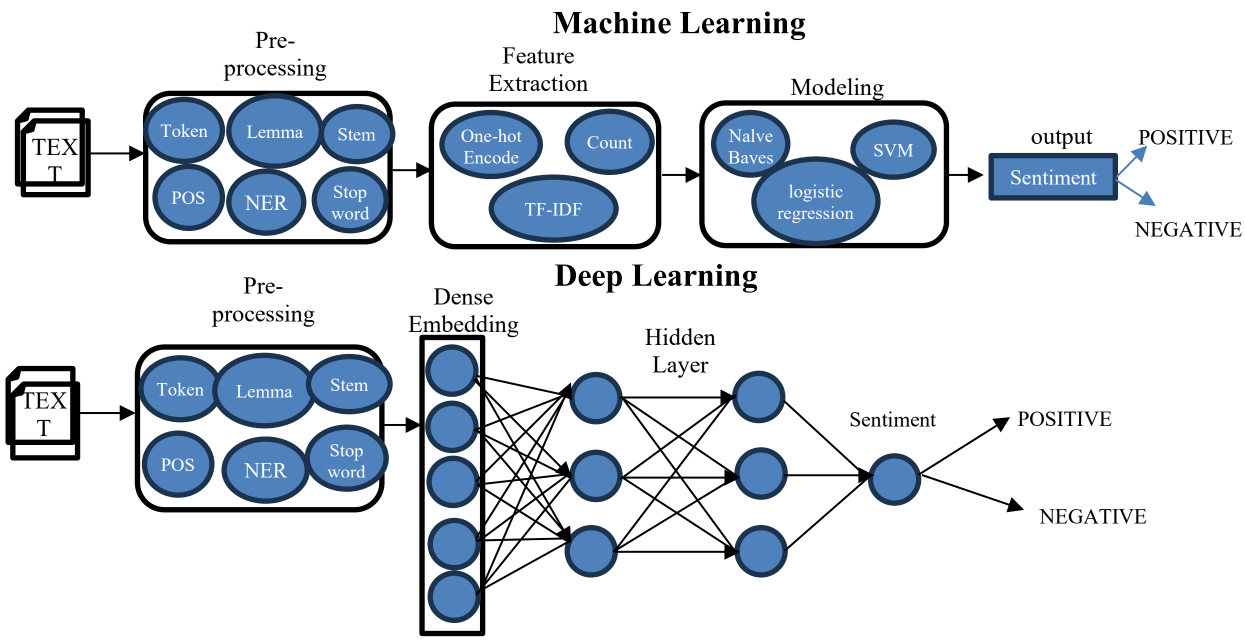


Figure 2. Differences between two classification approaches of sentiment polarity, machine learning (top), and deep learning (bottom) [Source 20]

When it comes to the neural network's hidden layers, deep learning takes a multilayer approach. Feature selection methods or manual feature definition are the mainstays of conventional machine learning systems. In contrast, deep learning models automatically learn and extract characteristics, leading to improved accuracy and performance. It is common practice to automatically measure the hyperparameters of classifier models as well. Figure 2 compares and contrasts deep learning with conventional machine learning methods for sentiment polarity categorization, such as Support Vector Machines (SVMs), Bayesian networks, and decision trees. Deep learning and artificial neural networks are now the go-to methods for a lot of issues in NLP, picture identification, and speech recognition.

Key Contribution

1. A new transfer deep learning model is presented, which incorporates cross-lingual embeddings to improve the sentiment analysis in both high-resource and low-resource languages.

2. The framework proposed has better accuracy than the classical models of sentiment analysis, with a high score of 96.42 accuracy on multilingual datasets and especially low-resource languages.

3. The study reveals how transfer learning can seem efficient in addressing the issue of data scarcity, and it is a scalable method to analyze the sentiment of multilingual languages, leading to the possibility of further language-specific models' improvement.

This article proposes a deep learning model of sentiment analysis in both high and low-resource languages. Section 1 presents the problem and motivation of the research, and Section 2 provides a review of existing literature on sentiment analysis and transfer learning. Section 3 is the challenges of low-resource language processing, and Section 4 is the proposed methodology. Section 5 will give the datasets used, such as Twitter data, and Section 6 will give the experimental results, comparing the proposed method with existing models. Section 7 summarizes the paper with major findings and research directions.

LITERATURE SURVEY

The computational and communicational aspects of sentiment analysis and transfer learning are thoroughly examined in this section. Emails, blog posts, tickets for assistance, web chats, social media, forums, and online comments are all examples of unstructured and organized online text that sentiment analysis tools can help collect information from and offer insightful observations on. Here is a look at the relevant research in sentiment analysis. The assessment also takes a broad look at the prior work in this area. Many different fields have found uses for sentiment analysis, which has led to considerable progress in the area.

One useful use of machine learning and natural language processing models is sentiment analysis. Both text-based & multimodal sentiment analysis, utilizing multiple data forms like text, audio, and video, have been thoroughly investigated in recent years, contributing to sentiment analysis's fast expansion and exploration throughout numerous fields. Research on sentiment analysis has focused on multiple methods. A system was created in the study to extract opinions from comments in telemedicine videos using a number of classifiers, such as Bayes Net, KNN, C4.5 Decision tree, Support Vector Machine (SVM), & SVM with Particle Swarm Optimization (SVM-PSO). When compared to other classifiers, the SVM-PSO classifier performed better when evaluating medical video reviews, with an accuracy of more than 80%. The rising interest in creating effective methods for these understudied languages is highlighted by current studies on sentiment evaluation for low-resourced languages. Popular methods include machine translation, transfer learning, and word embedding. Significant performance increases have been observed using deep learning frameworks, especially with pre-trained transformers. Results for African languages have been encouraging when using a combination of clustering approaches like GMMs and SVMs with neural network topologies like CNNs and Bidirectional Long Short-term Memory (Bi-LSTM).

The authors suggested a method for extracting sentiment from tweets based on their subject matter. In order to identify feelings connected to a particular issue, the model makes use of natural language processing methods. This study included three distinct approaches to sentiment identification: polarity-based classification, semantic association-based classification, and subjectivity-based classification. Among the several real-time applications used in a number of fields was sentiment analysis (SA). Natural language processing was used for feature extraction and classification in an effort to tackle MOLD_DL (Multilingual Aggressive Speech Detection using DL) methods. The purpose of implementing this FS was to use a fuzzy-based FCNN for data segmentation. Subsequently, a hybrid NB architecture with a support vector machine (SVM) was used to accomplish feature extraction and classification using the Bi-LSTM method's model. In hybrid DL algorithms were used to analyze people's tweets. SA was carried out using a five-point scale that encompasses neutral, extremely negative, highly positive, & negative. Out of the three approaches tested, Decision Trees (DT), Random Forest (RF), & Naive Bayes (NB) for classifying tweets, this one took the least amount of time to process the largest number of tweets, with the goal of improving word embeddings by the use of NLP approaches, a novel hybrid embedding method. Additionally, a new DL technique for obtaining features and a BiRNN for contextual and temporal feature application were introduced in this study.

The development of downstream natural language processing tasks, like sentiment analysis, has been dominated by PLMs based on the transformer architecture since the release of the BERT model, XLM-R, and RoBERTa. In comparison to models utilizing deep learning architectures, PLMs have regularly achieved state-of-the-art (SOTA) outcomes, demonstrating outstanding performance. There has been some discussion over whether or not these models work as well in low-resourced languages, despite the fact that they have shown outstanding results on sentiment analysis in languages with more resources.

Despite the abundance of deep transfer learning methods for text applications, no specialized review paper has yet been published about this field within the framework of transfer learning. A number of review articles, on the other hand, deal with different facets of transfer learning. An unlabeled dataset of Turkish political columns and tweets is used to apply the transfer learning approach. The suggested research gathered and transferred Twitter feature extractions for use in the Sentiment Analysis task's labelled data. Classification performance was also said to have improved. The article's authors used a transfer learning strategy to train a Deep Moji model that can detect sarcasm, emotions, and attitudes. Up to this point, they have shown that the extensive use of emojis in online conversations may also be leveraged to pre-train models, enabling them to extract and transfer sentiments from textual data to the intended domain. They utilize eight datasets across five domains, all using the same pre-trained construct. This approach has been proven to be effective and can get results that are on par with other ways. Topic and sentiment classification challenges were addressed in a different paper by presenting a bidirectional transformer architecture based on multi-Task learning. A number of datasets were used for simultaneous training, including AG News, Berkeley Sentiment Treebank (SST-2), & Movie Review (MR). They demonstrated incremental improvements compared to existing architectures. The authors also offer a transfer learning approach to sentiment analysis in another work, this time using a large dataset. After training a model to predict the positivity, negativity, or neutrality of a Twitter post, they utilized a pre-trained model to ascertain the tweet's sentiment intensity level across seven categories. Better results were achieved after using BiLSTM and transfer learning. As a practical transfer learning approach for performing NLP tasks, the researchers provide the Universal Language Model for Fine-tuning (ULMFiT) model in this article. They built a linguistic model with a large Wikipedia corpus and then refined it with the help of the IMDB dataset. With this paradigm, they demonstrated that all previously introduced solutions were beaten in both transfer training and current text categorization tests. A transfer learning methodology for the sentiment analysis task based on ULMFiT was presented in this study. Employing a Wikipedia-based pre-training model and then independently tuning the language model on two datasets, the Transfer Learning model performed better on both datasets.

To deal with domains with multiple sources and targets, the authors of this study suggest a probabilistic generating model of words. They made use of the transfer learning strategy, which is when knowledge gained in one area (the source domain) is used to enhance generalization in another (the target domain). Tasks involving document-level polarity classification have been successfully executed using data from several sources and target domains.

The literature review highlights the issue of sentiment analysis on low-resource languages (LRLs) because of poor data. It points out the role played by transfer learning (TL) and pre-trained models such as BERT and RoBERTa in sentiment classification, particularly in high-resource languages. Hybrid methods and deep learning prove promising in the research of LRLs, and TL can bridge the gap in data to transfer the knowledge of high-resource domains to improve the sentiment analysis in different languages.

MOTIVATION

Even though the data in both the source and the target domains are different, transfer learning enables the transfer of understanding from one domain to another (the target domain). One benefit of transfer learning compared to other learning paradigms, such as supervised learning, is that it can handle sparse training data in the area of interest by using information from a related but distinct domain to predict labels of unseen instances in the target domain. Unlike other ML algorithms, transfer learning can use information learnt from solving similar but previously completed tasks to improve predicted performance on new target tasks. This allows it to learn new tasks without any prior experience. As an example, consider sentiment analysis, which involves categorizing product reviews (for instance, laptops) as either good or negative. A large number of product reviews are required to train the classifier for this type of categorization activity. Data labeling, however, can be an incredibly expensive procedure. A classifier trained on camera evaluations, for instance, may be adapted to classify laptop reviews using transfer learning in this case. Transfer learning differentiates between a source domain, a target domain, and a source task, as opposed to a singular domain and a single task in traditional learning models. By utilizing the data provided by the source domain and optimizing the outcomes of the goal task, a model may be learnt from them. It has been said in the literature that there are various methods that can be used to achieve the transfer from the source to the target. It would want to emphasize this point. Analyzing text data is the main emphasis of this paper. Building a transfer learning framework to transfer sentiment analysis models between languages with abundant labeled data and those with less is the primary goal.

PROPOSED METHODOLOGY

Sentiment classification is a branch of natural language processing that identifies positive and negative aspects of subjective content. Document, sentence, and feature levels of analysis are all that's needed. Using the same classification algorithm in both high-resource and low-resource languages within the transfer learning framework. The model for any multi-domain and multilingual sentiment assessment technique consists of these components.

Step 1: Preparation of Data

Crucial information in order to get the dataset ready for analysis, pre-processing and cleaning are done during data preparation. Common pre-processing steps include removing any non-literal material and imprinting labels (for HTML pages). Leaving omitting review-related information that isn't essential for understanding the results, such as review dates & reviewers' identities.

Step 2: Review Analysis

Analyses literary aspects of reviews to find valuable information, like opinions and item features. Two common tag-based review analysis tasks are point-of-sale tagging and negation.

Step 3: Classifying Sentiments

Sentiment management is carried out following step 2 to attain the desired outcomes. The two-step procedure of classifying an opinionated archive as representing a general positive or negative attitude is called polarity grouping or presumptive polarity organization. Finding viewpoints and subjectivity are part of polarity characterization work. This usually means that there will be strong viewpoints in the next recordings. Still, there are instances where decide on a subject and then pick and choose which reports have subjective content and which portions of the archive contain subjective material. Figure 3 displays the model used by Twitter for sentiment analysis. It takes into consideration a contribution as a collection of literary reviews together with particular criteria, and then draws a conclusion based on the polarity of the positions taken by each review.

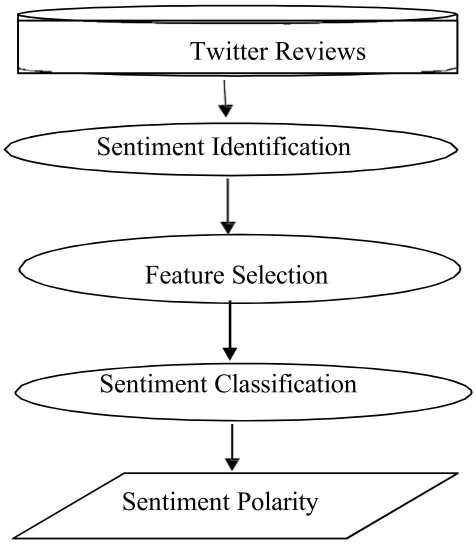


Figure 3. General process of sentimental analysis in transfer learning framework

There are two stages to the methodology's design in this section. Building a model for multimodal sentiment analysis using a Convolutional block attention module (CBAM) is the initial stage. In contrast, the second stage involves adding a hierarchical structure to the previously developed CBAM model in order to apply depressive Multimodal sentiment analysis. Third, adapt the sentiment analysis model for use in a system that supports more than one language.

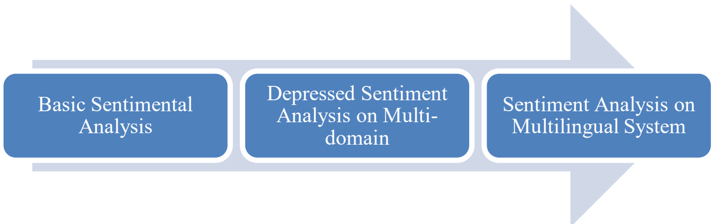


Figure 4. Steps for proposed methodology

This Figure 4 chart shows how the sentiment analysis activities will be conducted at various levels. The first is Basic Sentimental Analysis in which the general sentiment classification is carried out to establish whether or not the text is positive or negative. The second phase is Depressed Sentiment Analysis on Multi-domain which aims at determining depressive sentiments of different domains, which makes the analysis a bit more complicated as it deals with particular tones tied to emotion. Sentiment Analysis on Multilingual System is the last step, it is the extension of sentiment analysis to other languages, which allows the system to analyze various linguistic information and classify sentiment in different languages and cultures. The flowchart is a depiction of the rising complexity and expansion of sentiment analysis during the simple to multilingual and multi-domain environments.

Overview of Convolutional Block Attention Module (CBAM)

Any design of convolutional neural networks (CNNs) can incorporate the lightweight and general-purpose Convolutional Block Attention Module (CBAM). Figure 5 shows how CBAM iteratively infers attention maps over two dimensions channel and spatial to improve feature maps using attention mechanisms. CBAM consists of two modules:

- The Channel Attention Module differentiates the degree of importance on the time dimension
- The Spatial Attention Module assigns value to each decomposed sub-series

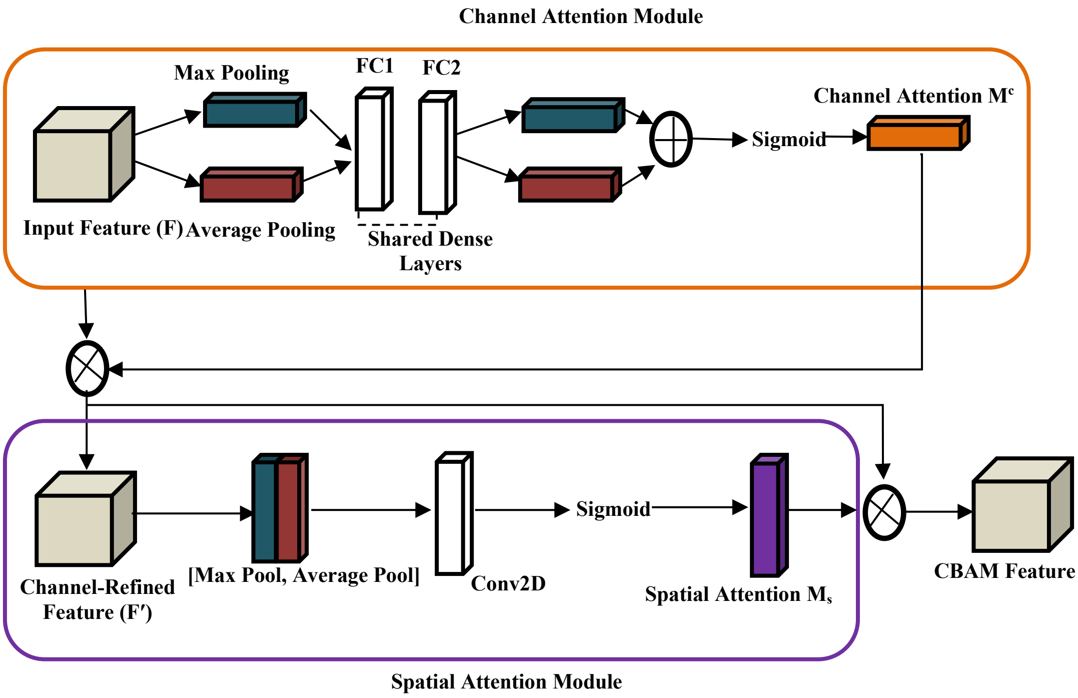


Figure 5. Basic CBAM architecture

The three primary parts of the proposed method are described in detail below. The proposed model's steps include building a word vector, finding deep aspect level features using an auto encoder, and finally, passing that information into a classifier to determine polarity. Algorithm 1 lays out the whole procedure.

Collection of Data

The data collection process involves gathering datasets from multiple domains, sourced from publicly available platforms. These datasets encompass diverse content to ensure comprehensive representation across various topics. The collected data is then organized and pre-processed for further analysis, ensuring it is ready for subsequent steps such as feature extraction, model training, and evaluation.

Pre-processing of Data

Sorting through primary sources is a must when working with original data. This step is called data pre-processing. Since commas & special symbols do not contribute to the phrase's or document's emotional worth, they are removed during pre-processing along with any unnecessary words in their opinion. Iteratively evaluating the acquired dataset, remove any unnecessary elements like URLs, special characters, commas, and additional punctuation marks, producing a clean dataset ready for further processing.

Optimizing and Extracting Weighted Features

Weighted extraction of features and optimization are performed after data pretreatment. The primary objective of this study is to present a methodical approach to feature extraction and selection for efficient and accurate subjective data classification. Consequently, the extraction and choice of features are both improved by the research. To get useful information out of clean data, you need to use a technique called feature extraction. One example is the extraction of weighted features. Figure 6 below shows the feature extraction process. It is necessary to optimize their retrieval and weighting of various attributes in order to obtain only the most essential ones. At this point, we've tied each possible data label—positive or negative score—to an optimized feature vector. A data dictionary is used to compute the score. In this step, TF-IDF is utilized for feature extraction. In a number of contexts, including textual analysis, the statistical likelihood of word frequency in a dataset can be ascertained using TF-IDF, which is the product of TF and Inverse Document Frequency.

It is mathematically evaluated as:

TF-IDF Formula: The overall TF-IDF for a term $t$in a document $d$within a corpus $C$is calculated as:

$$\text{TF-IDF}(t, d, C) = \text{TF}(t, d) \times \text{IDF}(t, C) \qquad (1)$$

In Equation 1, Where:

- $\text{TF}(t, d)$is the term frequency, which measures how often the term $t$appears in the document d.
- $\text{IDF}(t, C)$is the inverse document frequency, which measures how rare or common the term $t$is across the entire corpus C.

Term Frequency (TF): Term frequency measures the frequency of the term $t$in document d. It is calculated as the ratio of the number of times the term $t$appears in document $d$to the total number of terms in document d, represented as $\mid C \mid$:

$$\text{TF}(t, d) = \frac{f(t, d)}{\mid d \mid} \qquad (2)$$

In Equation 2, Where:

- $f(t, d)$is the frequency count of term $t$in document d.
- $\mid d \mid$is the total number of words (or tokens) in document d.

This gives the relative frequency of the term in the document, ensuring that the term's importance is scaled by the document's length.

Inverse Document Frequency (IDF): Inverse Document Frequency helps scale down the importance of terms that occur frequently across many documents in the corpus, and it boosts the importance of terms that are rare. The IDF of a term $t$is calculated as the logarithm of the ratio of the total number of documents $\mid C \mid$to the number of documents in which the term $t$appears:

$$\text{IDF}(t, C) = \log\left(\frac{\mid C \mid}{\mid \{d \in C \mid t \in d\} \mid}\right) \qquad (3)$$

In Equation 3, Where:

- $\mid C \mid$is the total number of documents in the corpus.
- $\mid \{d \in C \mid t \in d\} \mid$is the number of documents in which term $t$appears.

Operating on a Sentiment Level

To determine the polarity of sentiment in multilingual textual data, the sentiment-level procedure is employed. In this part, the suggested approach to the work is detailed. This section presents the operation at the sentiment level. Utilize TF-IDF for feature extraction. They are then put together to give a similar representation for words that mean the same thing. Part of speech tagging (PoST) is another tool used for POS occurrence extraction. Lastly, sentiment analysis also employs convolution auto encoders for deep feature extraction. After that, in order to further evaluate sentiment score, all of these features are blended to create hybrid features.

TF-IDF Vectorization

Natural language processing tasks form the basis of the proposed system architecture (Figure 6), which encompasses all phases of pre-processing and model training. The text datasets are used to train classification models, which are then used to create predictions based on the model with the highest accuracy. A representational technique to be employed for training the different categorization models is feature vectors. A word's score in a text is determined by its frequency of occurrence in the text and its likelihood of occurrence in texts belonging to other categories using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. This means that frequently occurring words in texts are penalized regardless of their categorization. It is now possible to train several classification models using these feature vectors. It is a method for de-identifying textual information. "Term Frequency" (TF) and "Inverse Document Frequency" (IDF) are acronyms for two related concepts. By combining inverted document frequency (IDF) with term frequency (TF), the TF-IDF vectorizer is created.

POS Occurrence Count

Every summary in this section distinguishes between different parts of speech for each word. The POS Tagger is used to extract the part-of-speech for each word. Tokens represent individual words in the phrase and are labeled with their POS, which might be anything from nouns to verbs to pronouns or even adverbs. Using the Stanford POS tagger, this study reduced the number of POS tags from 48 to 11. As mentioned earlier, this functionality makes use of the proposed CBAM Model to extract deep characteristics. The sentiment score evaluation then takes into account all of these factors.

CBAM Auto Encoder for Classification

When features have been extracted in order to find deep aspect level features, auto encoding is performed utilizing the CBAM Auto encoder, which stands for Convolution Block Attention Module. As mentioned before, CBAM is a basic attention module that might be utilized to enhance the extraction and classification of features process. Channel and spatial are the two main parts of the module. The module (CBAM) adaptively refines the map of characteristics derived from intermediaries at each network segmentation block. Information values are sorted into different groups using classification techniques. This study employs a classifier that uses a combination of lexical features and convolution auto-encoder features to categories review data into different opinion polarities. Here, lexical extraction of features and a stacked convolution auto encoder are input into the dataset before classification, after which it is turned into a word vector. In order to feed text into the system for feature extraction, it must first be turned into word vectors. In order to kick off the model, the extracted word vectors are utilized. Lexical characteristics and deep feature level data are used to train the classifier for polarity judgment.

Depression-Level Operation

At the depression level, in addition to adding the depression score, the features collected from the sentiment level are supplied into the operation. The method then presents three possible depression sentiment levels: high, low, and average, derived from a combination of the characteristics of the two levels. Here, establishes a list of 13 emotions for different languages with high and low resource availability; then use this list to determine the depression score that will be used to identify depressed attitudes. Classify these feelings as follows: empty, excitement, boredom, wrath, concern, joy, sadness, love, surprise, enjoyment, relief, hatred, and neutral. Among these negative sensations are concern, melancholy, hatred, emptiness, boredom, and wrath; among these pleasant sentiments are joy, love, fun, relief, and excitement. The depression score is assessed using the weighted average score. Figure 6 below shows the overall methodology.

This Figure 6 depicts how high-resource and low-resource languages (HRL and LRL) undergo sentiment analysis on an autoencoder classification method based on a CBAM. It starts with the collection of HRL and LRL data on a set of data, then weighted feature extraction and optimization. The information is subjected to TF-IDF vectorization and sentiment-level operations to change the text into an analyzable form. Then, POS (Part of Speech) occurrence verification verifies the appropriate features. Sentiment is then classified with the CBAM autoencoder-based classification model. Lastly, a depression level operation is done to determine the intensity of the sentiment used, in this case any depressive sentiment. The figure gives a summary of the process flow of analyzing and classifying sentiment of multilingual Twitter messages.

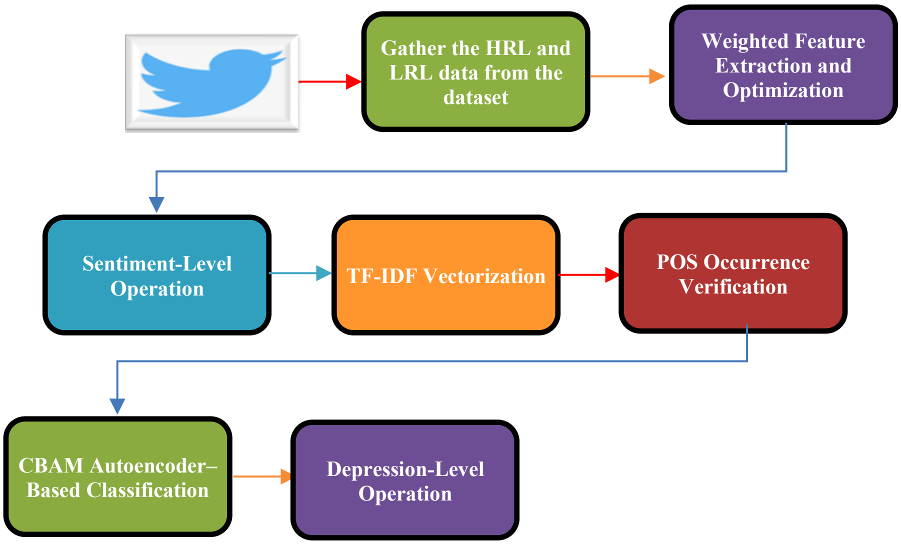


Figure 6. Proposed framework

Algorithm 1: Sentiment Classification using Transfer Learning with CBAM and TF-IDF

Input: Data{D}

Output: CBAM CR {Classification Result, -1=Negative,+1=Positive}

1: Start

2:PD←Pre-process(D) Where, PD= Gathered Information

3:TDv←TD(PD) Where, TD= term-frequency characteristic matrix

4:IDFv←IDF(PD) Where, IDF= product vector of inverse document-frequency

5: Separate into feature sets equal to (FV1, FV2, FVn)

6: When *cost* func converges, do

7: OFv= optimize {FV1,FV2,FVn}

8: Minimize(*cost* func)

9: Stop

10:CBAMv←Train{CBAM}

11:FFv←{IDFv, TDv, CBAMv}

12:CR←categorize {FFv}

13: Return CR, End

The algorithm 1 summarizes how sentiment can be classified over Convolutional Block Attention Module (CBAM) and transfer learning. It begins with preprocessing of the input data to extract and cleanse the appropriate data. The extractions of the features are computed as term-frequency (TD) and inverse document frequency (IDF) matrices. This data is further optimized into feature sets, which are optimized by minimizing the cost function to optimize the model. Once the CBAM model is trained using the optimized features, a final feature set (FF) is obtained by merging the outputs of the IDF, TD and CBAM. The model then grouped the sentiment as a positive sentiment or a negative sentiment. The output of this algorithm is the classification result.

DATASET DESCRIPTION

Moods like joy, anger, grief, and everything in between are being expressed by millions of individuals on Twitter. Taking this into account as a way people think is also important to sentiment analysis, which is all about identifying opinions, attitudes, assessments, and emotions. Emotions are categorized into positive and negative categories using sentiment analysis. These days, businesses are keen on using semantic analysis on textual data to get customer opinions on their wares. They rely heavily on sentiment analysis to gauge client happiness so they may tailor their offerings to meet their needs. They make an effort to retrieve data from social media networks in order to deal with text data. Google Plus, Facebook, and Twitter are just a few of the many social media platforms where users may voice their thoughts and feelings on a wide range of current events and issues. With an estimated 400 million users, micro blogging site Twitter is quickly becoming one of the most popular social media networking websites on the web. Launched in 2006, Twitter has quickly become the most well-known site for micro blogging. During a single hour in 2023, 15.6 million tweets were shared by 10 million individuals. Twitter is a micro blogging service where users express themselves through short messages called "tweets" posted on user accounts. A single tweet can only have 140 characters. Natural language processing (NLP) based sentiment analysis on Twitter. Tokenizing words and deleting stop words (such as "I," "me," "my," "our," "your," "is," "was," etc.) are some of the natural language processing techniques used for tweet text. Data preprocessing also makes use of natural language processing, which helps with tasks like text cleaning and punctuation mark removal. Using sentiment analysis, can learn how individuals are feeling about certain issues based on what they tweet about.

RESULT AND DISCUSSION

Simulations are conducted, and the sentiment analysis hybrid approach is implemented in the MATLAB (8.3.0) environment. The most recent configuration of the suggested method is used in the simulation in order to assess its performance. The MATrix Laboratory, or MATLAB for short, is a software suite for doing fast and simple logical calculations and I/O. Mathematica include a wealth of built-in functions for large-scale computations and a plethora of specialized toolboxes for many fields of study. As an example, PDEs, data analysis, statistics, and enhancement the answer. Packages, inheritance, pass-by-reference and pass-by-value languages, categories, and virtual dispatch are all concepts that MATLAB supports, in addition to the OOPS principle. But compared to other programming languages, its syntax and calling rules are very different. If the category handling has been done as a super-class, then the category is considered a reference category; otherwise, it is considered a worth category in MATLAB. The following are a few key aspects of MATLAB. When compared to other commercial processing products, MATLAB provides the most exact precision guarantee throughout all processing stages. Mathematica is a great tool for combining numerical calculations with visual representations. Due to MATLAB's interpretability, error rectification is a breeze.

Table 1. Parameter initialization for sentiment analysis model

Parameter	Range Value
Learning Rate (α)	0.001 - 0.1
Batch Size	32 - 256
Epochs	10 - 1000
Dropout Rate	0.1 - 0.5
Optimizer	Adam, SGD, RMSprop

This Table 1 presents the important parameters to be applied to initialize the sentiment analysis model, such as the learning rate, batch size, epochs, dropout rate, and optimizer. The table gives the range of values of each parameter which is important in the tuning of the performance of the model during the training process. These parameters affect the generalization capacity of the model, overfitting and optimal learning of the model.

Evaluation Metrics

Accuracy: Measures the proportion of correctly classified instances (both positive and negative) out of the total instances in equation 4.

$$\text{Accuracy} = \frac{\text{True Positives}+\text{True Negatives}}{\text{Total Instances}} \tag{4}$$

Precision: Measures the proportion of true positive predictions relative to the total predicted positives in equation 5.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}} \tag{5}$$

Recall (Sensitivity): Measures the proportion of true positive predictions relative to the actual positive cases in the dataset in equation 6.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}} \tag{6}$$

F1-Score: Harmonic mean of Precision and Recall, providing a balance between both metrics in equation 7.

$$\text{F1-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{7}$$

Compared the suggested Multilingual CBAM (MCBAM) to other hybrid algorithms, such as RNN, Bi-LSTM, Bi-GRU, and KMA. But K-means shows that the clustering problem can be solved by an unsupervised learning system. A classification model is trained using solely the clusters produced by K-Means. DRNN, biGRU, and biLSTM are Deep learning supervised classification methods. There was a comparison between the suggested work and well-known Deep Learning methods, such as clustering, classification, and the deep learning process Table 2.

Table 2. Results comparison of applying various algorithms on the twitter data set

Model	Accuracy	Precision	Recall	F1-Score
KMA	81.24	83.45	86.24	76.42
DRNN	83.45	87.24	88.54	81.23
Bi-GRU	88.57	89.26	90.47	84.56
Bi-LSTM	91.45	93.45	92.47	88.27
MCBAM	96.42	97.24	95.24	91.42

Experiments comparing the suggested MCBAM classifier to preexisting algorithms focused on different performance metrics are shown in Figure 7. As the dataset grows in size, so does the variation in accuracy, precision, recall, and F1-Score. With a range of 500 to 10,000 tweets, the data is presented. In comparison to the current techniques, the suggested MCBAM reaches above 95% in all parameters when the information count is 4000, whereas the latter only manages approximately 85%. At 7000 observations, the suggested classifier outperformed the state-of-the-art techniques by more than 95%. The system's performance also changes depending on the amount of remaining data. After comparing the suggested CBAM to the current algorithms, it is clear that it performs better. An additional tool for in-depth evaluation of the suggested method's efficacy on the Twitter dataset is the confusion matrix.

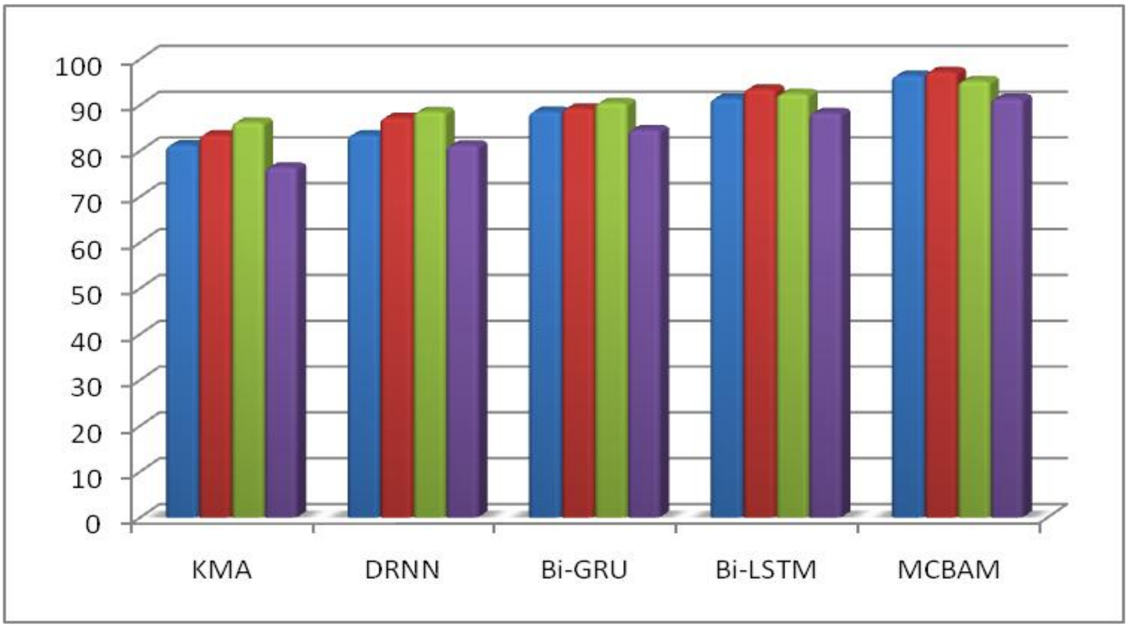


Figure 7. Comparative results of existing and proposed algorithms for multilingual sentimental classification

The ablation study was done to evaluate the effectiveness of major elements within the proposed transfer learning model (MCBAM) to sentiment analysis. Models that had certain components removed were tested in a study: cross-lingual embeddings, pre-trained models, and transfer learning. Findings indicated that the accuracy was lower without cross-lingual embeddings, and that they were significant in dealing with low-resource languages. Both training the model without pre-trained models and training the model on pre-trained models had a large negative effect on performance, highlighting the importance of pre-training to improve generalization. On the same note, removal of transfer learning led to worse performance, especially on low resource languages, which proves its usefulness in resolving the data scarcity. In general, the entire model (MCBAM) was more accurate, precise, recall, and F1-score than the conventional methods.

CONCLUSION

This study introduces a new model of transfer deep learning of sentiment analysis between the high-resource and low resource languages, which overcomes the problem of data insufficiency in low-resource languages. The major conclusions made by the research indicate that the use of cross-lingual embeddings, pre-trained models, and transfer learning are an enormous boost to the efficiency of sentiment analysis models. The suggested framework (MCBAM) is superior to the conventional models with an accuracy of 96.42, whereas Bi-LSTM and Bi-GRU give 91.45 % and 88.57 %, respectively. It means that the framework is very productive to work with the multilingual data and it helps the low-resource languages in particular.

The statistical knowledge indicates the significance of every part. In particular, in the ablation experiment, the removal of cross-lingual embeddings resulted in the reduction of accuracy, which shows their importance in the context of language bridging. The elimination of pre-trained models led to a serious decline in performance which underlines the importance of using pre-trained models to generalize. More so, without transfer learning, there is poorer performance particularly when dealing with low resource languages, justifying the role of transfer learning in data limitations elimination. The findings also indicate that the framework is an effective solution in improving sentiment analysis in multilingual datasets, including those with low resources.

There are a number of directions that can be taken in the future to improve sentiment analysis models. The next possible direction would be fine-tuning the offered model to particular regional languages, with the emphasis on the better performance of the model in underrepresented languages. Also, I would have included multilingual and multimodal information (e.g. text, audio and visual) as it would widen the applicability of the framework in various settings. Additional studies might also be devoted to the combination of domain-specific datasets to improve the sentiment analysis of specific industries or applications, including healthcare, finance, or politics to effectively deal with real-life issues.

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