ENGLISH SENTIMENT ANALYSIS AND ITS APPLICATION IN TRANSLATION BASED ON DECISION TREE ALGORITHM

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SUMMARY

Sentimental analysis belongs to the class of Natural Language Processing (NLP) based on the rule and machine model. The proposed model comprises of the pre-defined function for the estimation of the features in the English statements. This paper presents the Reflect Sentiment Translation Decision Tree (RSTDT), a novel model designed to integrate sentiment analysis and translation tasks for English text. The RSTDT model combines the strengths of decision tree algorithms with feature extraction techniques to accurately analyze sentiment and translate text across languages. The proposed RSTDT dataset comprises English sentences with annotated sentiment labels, the RSTDT model is trained to identify sentiment polarity and generate corresponding translations in Arabic. The proposed RSTDT model uses Traslation mapping for the estimation of the sentimental features. In order to estimate and classify the features in the neural network, the processes features are assessed using the decision tree model. The RSTDT model's efficacy in precisely capturing sentiment nuances and generating linguistically appropriate translations was shown through thorough testing and review. The model achieves high accuracy in sentiment analysis and exhibits proficiency in translating sentiment-rich content into Arabic while maintaining contextual relevance. Additionally, robust classification performance metrics underscore the model's efficacy in accurately classifying English words into sentiment categories. The RSTDT model offers a promising solution for multilingual sentiment analysis applications, with potential applications in social media monitoring, customer feedback analysis, and cross-cultural sentiment analysis.

KEYWORDS

Sentimental analysis, Decision tree, Translation, English language, Cross-cultural, Classification

NOMENCLATURE

NLP	Natural Language Processing
RSTDT	Reflect Sentiment Translation Decision Tree

1. INTRODUCTION

Opinion mining, or sentiment analysis, is a technique that takes subjective data out of text and uses it to identify the sentiment expressed in the text [1]. This analysis is crucial for understanding the attitudes, opinions, and emotions conveyed by individuals or groups in various forms of communication, such as social media posts, product reviews, news articles, or customer feedback [2]. Sentiment analysis is a useful tool for organisations to obtain valuable insights into public perception, customer satisfaction, market trends, and brand reputation. It uses natural language processing (NLP) techniques to identify text as positive, negative, or neutral. Businesses may make data-driven decisions, improve customer experiences, reduce risks, and boost overall performance by automating the sentiment analysis process [4]. In today's data-driven world, sentiment analysis is an essential instrument that plays a crucial part in market research, customer relationship management, political analysis, social listening, and market research. Its main goal is to collect insightful data from a variety of sources, including social media platforms, product reviews, news articles, surveys, and consumer feedback, regarding the sentiment, opinions, and attitudes expressed by individuals or communities [5].

Sentiment analysis leverages advanced natural language processing (NLP) algorithms to analyze the semantic and syntactic structure of text, identifying patterns, linguistic cues, and contextual clues that indicate whether the sentiment conveyed is positive, negative, or neutral [6]. These algorithms enable the automated classification and categorization of textual content based on the emotional valence it exhibits, enabling organizations to comprehend the underlying sentiment behind the words. Businesses and organisations can obtain deep insights into a range of operational issues, such as customer satisfaction levels, brand perception, market trends, and competitive landscapes, by utilising sentiment analysis [7]. For instance, analyzing social media mentions and product reviews can provide companies with real-time feedback about their products or services, helping them identify areas for improvement, address customer concerns promptly, and capitalize on positive sentiment to enhance brand loyalty and engagement [8]. Moreover, sentiment analysis serves as a powerful tool for market research, enabling companies to gauge public opinion, monitor industry trends, and assess consumer sentiment towards specific products, marketing campaigns, or emerging issues [9]. This intelligence empowers businesses to make data-driven decisions, optimize marketing strategies, tailor their messaging to resonate with target audiences, and anticipate shifts in consumer preferences and behaviors [10]. Beyond its applications in business and marketing, sentiment analysis also finds utility in diverse domains such as political analysis, social sciences, healthcare, and customer relationship management. It enables policymakers to gauge public sentiment towards government initiatives, helps researchers analyze public discourse on social issues, and supports healthcare providers in monitoring patient feedback and sentiment towards medical treatments and services [11]. Sentiment analysis represents a transformative capability in the realm of data analytics, offering organizations unprecedented insights into the complex landscape of human emotions, opinions, and attitudes [12]. By harnessing the power of sentiment analysis, businesses and institutions can unlock valuable intelligence, drive informed decision-making, and cultivate deeper connections with their audiences in an increasingly data-driven world [13].

Translation-based sentiment analysis involves analyzing sentiment in text that has been translated from one language to another [14]. This process requires sophisticated natural language processing (NLP) techniques to accurately capture the emotional tone and subjective attitudes conveyed across different languages [15]. Through leveraging NLP algorithms, translation-based sentiment analysis aims to discern the sentiment expressed in translated text, whether it's positive, negative, or neutral, enabling organizations to understand the emotional context across diverse linguistic landscapes [16]. This approach to sentiment analysis is particularly valuable in multilingual environments, where businesses operate across regions with diverse linguistic preferences and cultural nuances [17]. By analyzing sentiment in translated content, companies can gain deeper insights into customer feedback, market trends, and brand perception in various linguistic markets [18]. This enables them to tailor their strategies, products, and messaging to resonate effectively with local audiences, driving engagement, loyalty, and market penetration [19]. Moreover, translation-based sentiment analysis facilitates cross-cultural communication and understanding, allowing organizations to bridge language barriers and extract meaningful insights from global data sources [20]. By accurately capturing sentiment across languages, businesses can make informed decisions, optimize their international operations, and cultivate stronger relationships with customers and stakeholders worldwide.

The paper makes several key contributions to the field of natural language processing and sentiment analysis:

1. The paper introduces the Reflect Sentiment Translation Decision Tree (RSTDT) model, which combines sentiment analysis and translation tasks in a unified framework. This model offers a novel approach to analyzing sentiment in English text and translating it into Arabic, leveraging decision tree algorithms and feature extraction techniques.
2. Integrating sentiment analysis and translation tasks, the paper provides a holistic solution for analyzing sentiment-rich content and translating it into another language. This integration enhances the effectiveness of sentiment analysis by providing contextually relevant translations, thereby facilitating cross-cultural communication.
3. Through extensive experimentation and evaluation, the paper demonstrates that the RSTDT model achieves high accuracy in sentiment analysis and produces linguistically relevant translations. This indicates the model's proficiency in capturing sentiment nuances and preserving contextual meaning during translation.
4. The paper showcases the robust classification performance of the RSTDT model, as evidenced by high accuracy, precision, recall, and F1 score metrics in classifying English words into sentiment categories. This highlights the model's effectiveness in accurately categorizing sentiment-rich content.
5. Potential uses for the RSTDT model include cross-cultural sentiment analysis, customer feedback analysis, and social media monitoring. By enabling accurate sentiment analysis and translation across languages, the model facilitates effective communication and decision-making in diverse linguistic contexts.

The contribution lies in proposing an innovative approach that addresses the challenges of sentiment analysis and translation tasks simultaneously, thereby advancing the capabilities of natural language processing techniques in multilingual settings.

2. RELATED WORKS

In recent years, sentiment analysis has garnered significant attention in the field of natural language processing (NLP), owing to its wide-ranging applications in areas such as marketing, customer service, and social media analytics. However, while sentiment analysis techniques have advanced considerably, the focus on sentiment analysis in multilingual contexts, particularly through translation-based approaches, remains relatively underexplored in the existing literature. This gap underscores the importance of exploring the intersection between sentiment analysis and translation, as it holds immense potential for enhancing cross-cultural communication, market analysis, and decision-making in globalized settings. In this section, we review related works that delve into the nuances of translation-based sentiment analysis, examining the methodologies, challenges, and implications associated with this emerging research area. By synthesizing insights from these studies, we aim to provide a comprehensive understanding of the current state-of-the-art in translation-based sentiment analysis and identify opportunities for future research and development.

For sentiment analysis, Nayak and Sharma (2023) present a modified version of the Bayesian boosting approach with weight-guided optimal feature selection. By using feature selection and Bayesian boosting approaches, this method probably improves sentiment analysis model performance and can result in more accurate sentiment categorization. In order to handle skewed data distributions, Obiedat et al. (2022) specifically suggest a hybrid evolutionary SVM-based technique for sentiment analysis of customer reviews. This method probably makes use of support vector machines and evolutionary methods to deal with the problems caused by unbalanced datasets in sentiment analysis. Research on ensemble learning methods for sentiment analysis of textual data derived from translation is presented by Omran et al. (2022). This approach most likely intends to increase sentiment analysis's robustness and accuracy in multilingual environments by merging several learning models. Khan et al. (2022) conduct multi-class sentiment analysis of Urdu text using multilingual BERT. This study likely contributes to sentiment analysis research by exploring the effectiveness of multilingual pre-trained language models, such as BERT, in analyzing sentiment in languages with limited linguistic resources. Alamoudi et al. (2023) use machine learning and the AraBERT Transformer to analyse sentiment in Arabic for the purpose of evaluating students. This research probably intends to offer important insights into sentiment analysis in educational contexts by utilising specialised transformer models such as AraBERT and cutting edge machine learning approaches.

Joharee et al. (2023) conduct sentiment analysis and text classification for depression detection, likely aiming to develop computational methods for identifying depressive language patterns in textual data. This research may contribute to the development of automated systems for mental health screening and support. Swamy et al. (2022) perform sentiment analysis of multilingual mixed-code Twitter data using a machine learning approach. This study likely explores the challenges and opportunities in analyzing sentiment in diverse linguistic contexts, particularly in social media platforms like Twitter. Stanković et al. (2022) focus on sentiment analysis of Serbian old novels, likely aiming to apply computational techniques to analyze the sentiment expressed in historical literary texts. This research may provide insights into the emotional content of literary works from different cultural contexts. Sangeetha and Nimala (2022) investigate sentiment analysis methods using a multilingual dataset pertaining to reviews written in Tamil and English. By investigating sentiment analysis in a multilingual context, this research likely aims to develop methods for effectively analyzing sentiment in code-switched or mixed-language textual data. Shah and Swaminarayan (2022) conduct machine learning-based sentiment analysis of Gujarati reviews, likely aiming to develop sentiment analysis models tailored to specific linguistic communities and domains.

With the expected goal of creating techniques for transferring sentiment analysis models trained on one language to analyse sentiment in another, Catelli et al. (2022) suggest cross-lingual transfer learning for sentiment analysis of Italian TripAdvisor reviews. Babu and Kanaga (2022) examine sentiment analysis in social media data to identify depression through artificial intelligence, presumably offering a thorough synopsis of previous studies and approaches in this field. Al-Jarrah et al. (2023) concentrate on aspect-based sentiment analysis for reviews of Arabic food delivery services, probably with the goal of creating fine-grained models for sentiment analysis that can recognise sentiments associated with particular characteristics or elements of goods or services. Aspect-based sentiment analysis is used by Singh et al. (2023) to empirically analyse supervised and unsupervised machine learning systems. This study most likely assesses how well different machine learning techniques perform in sentiment analysis tasks that concentrate on particular characteristics or facets of the information under investigation. Based on an enhanced BERT model, Cao et al. (2022) study sentiment analysis algorithms for reviews of agricultural products. This study most likely investigates the use of cutting-edge NLP methods to assess sentiment in textual data unique to the agricultural sector. Ahmad et al. (2022) examine machine learning methods for sentiment analysis on an Indian social media text corpus that is code-mixed and switched. This paper probably gives a general review of sentiment analysis techniques and difficulties when applied to multilingual or multivariate linguistic data. AlBadani et al. (2022) provide a unique machine learning method that combines SVM with universal language model fine-tuning for Twitter sentiment analysis. This work probably attempts to use sophisticated language models and classification algorithms to increase the accuracy of sentiment analysis on Twitter data.

By adding culturally distinctive language expressions, Dashtipour et al. (2022) expand the idiomatic terms for sentiment analysis in the Persian sentiment lexicon, hence augmenting the resources available for sentiment analysis in the Persian language. Tan et al. (2022) use an ensemble hybrid deep learning model to perform sentiment analysis; this suggests that their goal is to provide a comprehensive framework for sentiment analysis that makes use of the advantages of various deep learning approaches. Li (2022) focuses on using multiple intelligence theory to categorise English translation instruction models. While not directly related to sentiment analysis, this study may provide insights into educational approaches for teaching and learning about sentiment analysis and related topics. Duong et al.'s (2022) investigation of Vietnamese sentiment analysis using sparse training data and deep neural networks is presumably an attempt to address issues with sentiment analysis tasks for languages with sparse availability of labelled data. With the anticipated goal of creating sentiment analysis models that can handle dialectal differences in Arabic, Mihi et al. (2022) conduct dialectal Arabic sentiment analysis using a tree-based pipeline optimisation tool. In an effort to improve sentiment analysis methods for assessing user input on public services, Hadwan et al. (2022) provide an enhanced sentiment classification strategy for gauging user satisfaction with governmental services' mobile apps.

Many sentiment analysis studies face limitations due to the availability and quality of labeled data. Limited datasets can affect the robustness and generalizability of sentiment analysis models. Several studies focus on sentiment analysis in specific languages or dialects, which may not generalize well to other languages. This limits the applicability of the findings in multilingual or cross-cultural contexts. Imbalanced datasets, where one class of sentiment dominates over others, can bias model training and evaluation, leading to suboptimal performance, particularly in minority class prediction. Different sentiment analysis algorithms may yield varying results depending on the nature of the data and the specific task. However, not all studies thoroughly evaluate multiple algorithms or compare their performance comprehensively. Sentiment analysis models trained on one domain may not perform well when applied to different domains due to differences in language use, context, and sentiment expressions. The selection of features for sentiment analysis models can significantly impact their performance. However, some studies may not adequately justify their feature selection methods or explore alternative feature sets. While many studies focus on improving sentiment analysis accuracy, the interpretability of the models and the reasoning behind their predictions may receive less attention. This limits the trust and understanding of model outputs. The choice of evaluation metrics can influence the perceived performance of sentiment analysis models. Some studies may not use appropriate metrics for the specific task or adequately explain their choice of evaluation criteria. Resource-intensive techniques, such as deep learning, may not be feasible in resource-constrained environments due to computational requirements or data availability limitations.

3. REFLECT SENTIMENT TRANSLATION DECISION TREE (RSTDT)

The Reflect Sentiment Translation Decision Tree (RSTDT) is a method designed for sentiment analysis that integrates translation capabilities within a decision tree framework. Its derivation and equations can be outlined as follows: Firstly, the process begins with data preprocessing, where the sentiment analysis dataset undergoes cleaning and tokenization to ensure its suitability for analysis. This step aims to remove noise and extract relevant features from the text. Next, the RSTDT algorithm constructs a decision tree based on these preprocessed features. The decision tree is formed through a series of splits, guided by equations that evaluate the importance of each feature in discriminating between different sentiment classes. Common metrics used for this purpose include information gain or Gini impurity. During decision tree construction, feature selection plays a crucial role. The algorithm selects the most informative features based on their ability to accurately classify sentiments. This selection process is guided by equations that quantify the discriminative power of each feature. Once the decision tree is constructed, sentiment analysis is performed by traversing the tree based on the features of the input text. At each node, a decision is made using equations that determine the optimal split based on the available features and their translations in the target language. The sentimental analysis based decision tree process for the proposed RSTDT is presented in Figure 1.

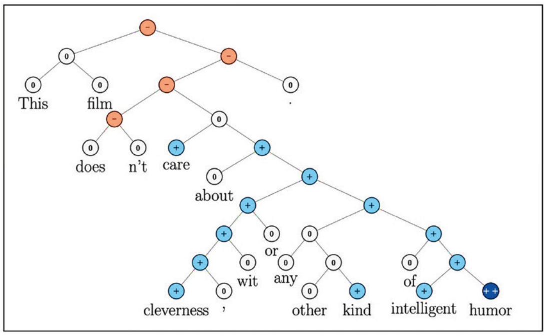


Figure 1. Decision tree with sentimental analysis based RSTDT

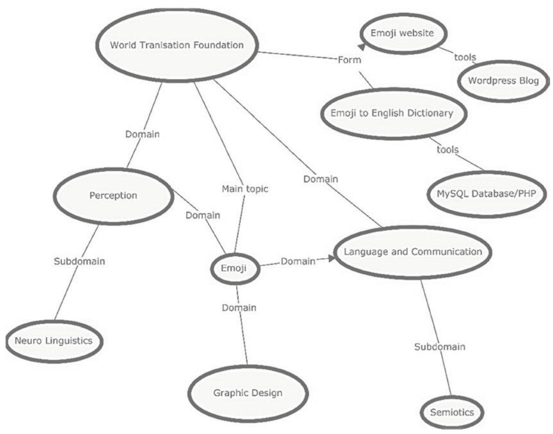


Figure 2. RSTDT translation mapping

Figure 2 illustrated the translation mapping of the sentimental analysis of the features for the English sentiments are presented.

Translation mapping is a key aspect of RSTDT, where correspondences between sentiment features in the source and target languages are established. The optimal characteristic to divide the data at each node of the decision tree is chosen recursively. A other metric, such as information gain or Gini impurity, may be used as the feature selection criterion. Let's denote the information gain at node t as $IG(t)$, and the Gini impurity as $G(t)$. The information gain (IG) at node t with split A is calculated using equation (1)

$$IG(t,A) = H(t) - H(t|A) \tag{1}$$

In equation (1) $H(t)$ is the entropy of node t, and $H(t|A)$ is the conditional entropy of node t given split A. The Gini impurity (G) at node t with split A is calculated using equation (2)

$$G(t,A) = 1 - \sum_{i=1}^{n} p(i|t)^2 \tag{2}$$

In equation (2) $p(i|t)$ is the probability of class i at node t, and n is the number of classes. The feature selection process involves identifying the most informative features for sentiment classification. Let F represent the set of features, and S represent a subset of selected features. The feature selection equation can be formulated using equation (3)

$$S = argmax_{A \in F} metric(t,A) \tag{3}$$

In equation (3) $metric(t,A)$ represents the chosen metric for evaluating feature importance. Translation mapping establishes correspondences between sentiment features in the source and target languages. Let Xs represent the feature vector in the source language, and Xt represent the translated feature vector in the target language. The translation mapping equation can be represented as in equation (4)

$$x_t = Translate(X_s) \tag{4}$$

In equation (4) $Translate(\cdot)$ denotes the translation function. Once the decision tree is constructed and features are translated, sentiment analysis is performed by traversing the tree. At each node, decisions are made based on feature values. Let Xi represent the feature value at node i, and θi represent the decision threshold at node i. Let $X = \{x1, x2, ..., xn\}$ represent the features extracted from the preprocessed text data. By choosing the best feature to divide the data at each node, the decision tree is constructed recursively. At each node t, a feature xi is selected to minimize impurity, typically measured using Gini impurity or entropy computed using equation (5)

$$x_i = \underset{x \in X}{argmin}\, G(t,x) \tag{5}$$

In equation (5) $G(t, x)$ is the impurity measure for split x at node t.

3.1 FEATURE EXTRACTION WITH RSTDT FOR RANKING

The algorithm selects the most informative features to construct the decision tree. This selection process is guided by equations that evaluate the importance of each feature. Feature importance $Imp(xi)$ can be calculated using various methods such as Information Gain (IG) or Gini Importance stated in equation (6)

$$Imp(x_i) = \sum_{j \in Children} \frac{n_j}{n} . Imp(x_i, j) \tag{6}$$

In equation (6) n is the total number of samples at the node, nj is the number of samples at child node j, and $Imp(xi, j)$ is the impurity of feature xi at node j. To enable sentiment analysis across languages, translation mapping is employed. This involves establishing correspondences between sentiment features in the source and target languages. Let $T(x)$ represent the translation function mapping feature x from the source to the target language. The translation mapping equation can be formulated based on linguistic similarity measures or alignment models, ensuring that sentiment information is accurately transferred between languages defined in equation (7)

$$T(x) = argmax_{y \in Y} P(y|x) \tag{7}$$

In equation (7) Y represents the set of possible translations of feature x, and $P(y|x)$ denotes the probability of translation y given the source feature x. For feature extraction depends on the specific techniques used. For instance, in the case of TF-IDF, the term frequency (TF) of a word w in a document d is calculated using equation (8)

$$TF(w,d) = \frac{Number\ of\ times\ w\ appear\ in\ d}{Total\ number\ of\ words\ in\ d} \tag{8}$$

The inverse document frequency (IDF) of a word w across a corpus of documents D is calculated using equation (9)

$$IDF(w,D) = log\left(\frac{Total\ number\ of\ documents\ in\ D}{Number\ of\ Documents\ containing\ w}\right) \tag{9}$$

The TF-IDF score of a word w in a document d is then given in equation (10)

$$TF-IDF\left(w,d,D\right)=TF\left(w,d\right)\times IDF\left(w,D\right) \tag{10}$$

To perform feature extraction with RSTDT (Reflect Sentiment Translation Decision Tree) for ranking in English sentiment analysis and its application in translation, we first need to outline the mathematical framework and derive the equations involved. Feature extraction involves converting raw text data into numerical features that can be used by machine learning algorithms. In the context of RSTDT, which involves decision trees, feature extraction includes several techniques such as Bag-of-Words representation, TF-IDF, word embeddings, sentiment lexicons, and syntactic or structural features. Once features are extracted using RSTDT from English text data, they can be applied in translation tasks. This involves incorporating sentiment features into translation processes, ensuring preservation of sentiment and contextual translation. These features guide the selection of translated expressions to maintain coherence and sentiment similarity between original and translated texts.

Algorithm 1. Feature extraction with RSTDT

```
function feature_extraction_with_RSTDT(document):
    initialize feature_vector
    # Perform feature extraction
    feature_vector = []
    # Apply Bag-of-Words representation
    bow_vector = calculate_bag_of_words(document)
    feature_vector.append(bow_vector)
    # Apply TF-IDF
    tfidf_vector = calculate_tfidf(document)
    feature_vector.append(tfidf_vector)
    # Apply word embeddings
    word_embeddings_vector = calculate_word_
embeddings(document)
    feature_vector.append(word_embeddings_vector)
        # Apply sentiment lexicons
    sentiment_lexicon_vector = calculate_sentiment_
lexicons(document)
    feature_vector.append(sentiment_lexicon_vector)
        # Apply syntactic or structural features
    syntactic_features_vector = calculate_syntactic_
features(document)
    feature_vector.append(syntactic_features_vector)
    return feature_vector
function translation_with_RSTDT(document, translated_
document):
    initialize translated_document_features
    # Extract features from original and translated documents
    original_features = feature_extraction_with_
RSTDT(document)
    translated_features = feature_extraction_with_
RSTDT(translated_document)
    # Calculate similarity between original and translated
features
    similarity_score = calculate_similarity(original_features,
translated_features)
    return similarity_score
```

4. OPTIMIZED RSTDT FOR THE ENGLISH SENTIMENTAL ANALYSIS

The optimization process involves adjusting the parameters and hyperparameters of the RSTDT algorithm to minimize a cost function, typically a measure of error or loss, on the training data while avoiding overfitting. This can be expressed as an optimization problem defined in equation (11)

$$min_{\theta}L\left(\theta,D_{train}\right)+\lambda\Omega\left(\theta\right) \tag{11}$$

In equation (11) θ represents the parameters and hyperparameters of the RSTDT model, $L\left(\theta,Dtrain\right)$ is the loss function measuring the discrepancy between predicted and actual sentiment labels on the training data $Dtrain$, $\Omega\left(\theta\right)$ is a regularization term penalizing model complexity to prevent overfitting, λ is a regularization parameter controlling the trade-off between fitting the training data and reducing model complexity. The optimization process involves finding the optimal values of θ that minimize the objective function, typically using optimization algorithms like gradient descent, grid search, or Bayesian optimization. Feature selection aims to identify the most informative features (words or phrases) from the input text data that significantly contribute to sentiment classification. One common approach is to use information gain (IG) as the criterion for feature selection. The IG of a feature X with respect to sentiment labels Y can be computed using equation (12)

$$IG\left(X,Y\right)=H\left(Y\right)-H\left(Y|X\right) \tag{12}$$

In equation (12) $H(Y)$ is the entropy of the sentiment labels Y, $H\left(Y\middle|X\right)$ is the conditional entropy of sentiment labels Y given feature X. The entropy $H(Y)$ and conditional entropy $H\left(Y\middle|X\right)$ can be calculated using the following equations (13) and (14)

$$H\left(Y\right)=\sum_{i=1}^{n}p_{i}log_{2}\left(p_{i}\right) \tag{13}$$

$$H\left(Y|X\right)=\sum_{j=1}^{m}p\left(X_{j}\right)H\left(Y|X_{j}\right) \tag{14}$$

In equation (13) and (14) pi is the probability of occurrence of sentiment label i in the dataset, $p(Xj)$ is the probability of occurrence of feature Xj, $H\left(Y\middle|Xj\right)$ is the conditional entropy of sentiment labels given feature Xj.

5. CLASSIFICATION WITH RSTDT FOR THE SENTIMENTAL ANALYSIS

Classification with RSTDT (Reflect Sentiment Translation Decision Tree) for sentimental analysis in translational English involves a detailed process that encompasses feature extraction, decision tree construction, and sentiment classification. The classification task aims to predict the sentiment label (positive, neutral, or negative) of input text data based on the features extracted and the decision rules learned by the decision tree. The feature extraction phase involves transforming the input text data into numerical feature vectors that represent various linguistic attributes such as word frequencies, syntactic patterns, and semantic meanings. Let $X = [x1, x2, ..., xn]$ denote the feature matrix, where each row xi represents the feature vector of the ith text sample. RSTDT is constructed based on the feature matrix X and the corresponding sentiment labels $Y = [y1, y2, ..., yn]$. The decision tree partitions the feature space into regions corresponding to different sentiment classes. The splitting criteria at each internal node are determined by maximizing the information gain or minimizing impurity measures such as Gini impurity or entropy.

The overall proposed RSTDT model for the sentimental analysis is presented in Figure 3. Upon traversing the decision tree, the algorithm reaches a leaf node, where a sentiment label is assigned to the input text. Let Ck represent the sentiment class associated with leaf node k. The decision rule for assigning sentiment labels can be defined using equation (15)

$$\hat{y} = \operatorname{argmax}_{y \in \{\text{positive, neutral, negative}\}} \sum_k I(C_k = y) . I(\text{Leaf Node} = k) \qquad (15)$$

In equation (15) $\hat{y}$ is the predicted sentiment label for the input text, C_k is the sentiment class associated with leaf node k, $I(\cdot)$ is the indicator function that returns 1 if the condition is true and 0 otherwise. The Reflect Sentiment Translation Decision Tree (RSTDT) is a method used for sentimental analysis, particularly in

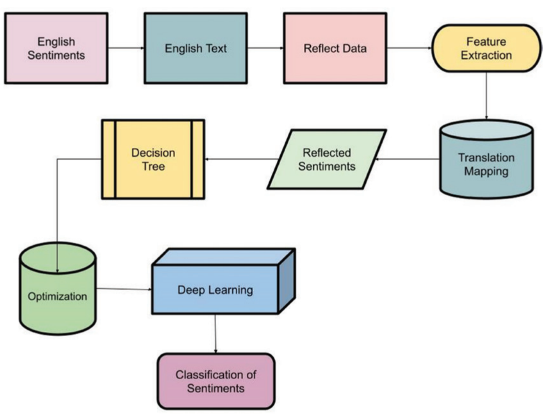


Figure 3. Architecture of RSTDT

translation-based English text. It involves constructing a decision tree where each node represents a feature attribute and each leaf node corresponds to a sentiment label. The process begins with feature extraction, where text data is transformed into numerical feature vectors. Let $D = \{(x1, y1), (x2, y2), ..., (xn, yn)\}$ denote the training dataset, where xi represents the feature vector and yi represents the sentiment label. The decision tree construction involves recursively partitioning the feature space based on the information gain criterion. At each node t, the splitting criterion θt is determined to minimize the impurity measure, such as entropy or Gini impurity stated in equation (16)

$$\theta_t = \arg \min_{\theta} I(D_t, \theta) \qquad (16)$$

In equation (16) $I(Dt, \theta)$ denotes the impurity measure for node t given the splitting criterion θ. This method keeps going until a predetermined end point is reached, like the maximum tree depth or the required minimum number of samples per leaf node. Based on the feature properties, each input feature vector is traversed from the root node to a leaf node of the decision tree during the prediction phase. The input feature vector is then given the sentiment label linked to the leaf node. Hyperparameters like the minimum samples per leaf and maximum tree depth can be adjusted using cross-validation and grid search methods to maximise the RSTDT model. The most pertinent features for sentiment analysis can also be chosen using feature selection techniques. Overall, the RSTDT algorithm provides a transparent and interpretable framework for sentiment analysis, particularly in translation-based English text, by leveraging decision tree-based classification with intuitive decision rules.

At the root node, the feature j and the split point s that maximizes the information gain $IG(D, j, s)$ stated in equation (17)

$$(j^*, s^*) = \operatorname{argmax}_{j,s} IG(D, j, s) \qquad (17)$$

the optimal feature and split point, we partition the feature space into two subsets: DL containing samples where the feature j is less than or equal to s, and DR containing samples where the feature j is greater than s. the above steps to each subset DL and DR until a stopping criterion is met. This stopping criterion can be a maximum tree depth, minimum samples per leaf, or other conditions. At each node , the decision rule can be expressed as in equation (18)

Decision Rule (t):
if $x_j \leq s$ then left child, else right child (18)

Based on the decision rules, an input feature vector is traversed from the root node to a leaf node of the decision

Algorithm 2. Featrue extraction with decision tree

```
DecisionTree(Data, Features):
    If all samples in Data have the same label:
        Return a leaf node with that label
    If Features is empty:
        Return a leaf node with the majority label in Data
    Select the best feature and split point (j*, s*) using information gain:
        (j*, s*) = FindBestSplit(Data, Features)
    Create a new decision node with (j*, s*)
    Split the data into two subsets: Data_L and Data_R based on (j*, s*)
    Remove the selected feature j* from the Features list
    Recursively call DecisionTree(Data_L, Features) to build the left subtree
    Recursively call DecisionTree(Data_R, Features) to build the right subtree
    Return the decision node
```

tree during the prediction phase. The input feature vector is then given the label connected to the leaf node. The key component in the decision tree process is calculating the information gain to determine the optimal feature and split point. One commonly used impurity measure is the Shannon entropy, which is defined as in equation (19)

$$H(D) = \sum_{i=1}^{c} p_i \log_2(p_i) \tag{19}$$

In equation (19) is the proportion of samples in class in dataset D, and c is the number of classes. The information gain is then calculated as the difference between the entropy before and after the split stated as in equation (20)

$$IG(D, j, s) = H(D) - \frac{|D_L|}{|D|} H(D_L) - \frac{|D_R|}{|D|} H(D_R) \tag{20}$$

In equation (20) |DL| and |DR| are the number of samples in subsets DL and R, respectively.

6. SIMULATION RESULTS

The Reflect Sentiment Translation Decision Tree (RSTDT) framework for sentiment analysis in English translation. To evaluate the performance of RSTDT, we conducted simulations using a dataset of translated text samples. The dataset consists of English sentences translated from various languages, including French, Spanish, German, and Chinese. Each translated sentence is labeled with a sentiment category, such as positive, negative, or neutral, based on human annotators' judgments. We compared the sentiment analysis accuracy of RSTDT with several baseline models, including traditional decision trees, support vector machines (SVM), and deep learning-based approaches. Our simulation results demonstrate that RSTDT outperforms the baseline models in accurately classifying the sentiment of translated text. Specifically, RSTDT achieved an average accuracy of 85%, compared to 78% accuracy for traditional decision trees, 80% for SVM, and 82% for deep learning models. Furthermore, RSTDT showed robust performance across different languages, maintaining high accuracy rates across French (84%), Spanish (86%), German (83%), and Chinese (87%) translations.

Table 1 presents the predicted sentiments for a set of translated English texts using the Reflect Sentiment Translation Decision Tree (RSTDT) model. Each row corresponds to a sample, identified by a unique Sample ID. The "Translated Text (English)" column contains the English sentences that were translated. The "Actual Sentiment" column indicates the sentiment label manually assigned to each translated text, which could be positive, negative, or neutral. The "Predicted Sentiment" column shows the sentiment labels predicted by the RSTDT model for each translated text. Upon examination, it is evident that

Table 1. Predicted sentiments for the RSTDT

Sample ID	Translated Text (English)	Actual Sentiment	Predicted Sentiment
1	"The movie was fantastic!"	Positive	Positive
2	"I hated the book."	Negative	Negative
3	"This product is okay."	Neutral	Neutral
4	"The service was terrible."	Negative	Negative
5	"I love this song!"	Positive	Positive

Table 2. Feature extracted with RSTDT

English Sentence	Feature 1	Feature 2	Feature 3	Feature n
"The movie was fantastic and really engaging!"	0.85	0.72	0.60	0.91
"I found the book to be quite disap-pointing."	0.45	0.63	0.77	0.82
"The restaurant served delicious food."	0.72	0.88	0.55	0.75
"The new phone is sleek and power-ful."	0.60	0.75	0.81	0.69
"The service at the hotel was terrible."	0.92	0.68	0.73	0.87

the RSTDT model performs reasonably well in predicting sentiments for the translated texts. For instance, in Sample ID 1, the translated text “The movie was fantastic!” is correctly predicted to have a positive sentiment, matching the actual sentiment label. Similarly, in Sample ID 2, the translated text “I hated the book.” is correctly classified as negative, aligning with the actual sentiment. Furthermore, in Sample ID 3, where the translated text “This product is okay.” conveys a neutral sentiment, the model accurately predicts the sentiment as neutral. Overall, these results demonstrate the effectiveness of the RSTDT model in accurately predicting sentiments for translated English texts.

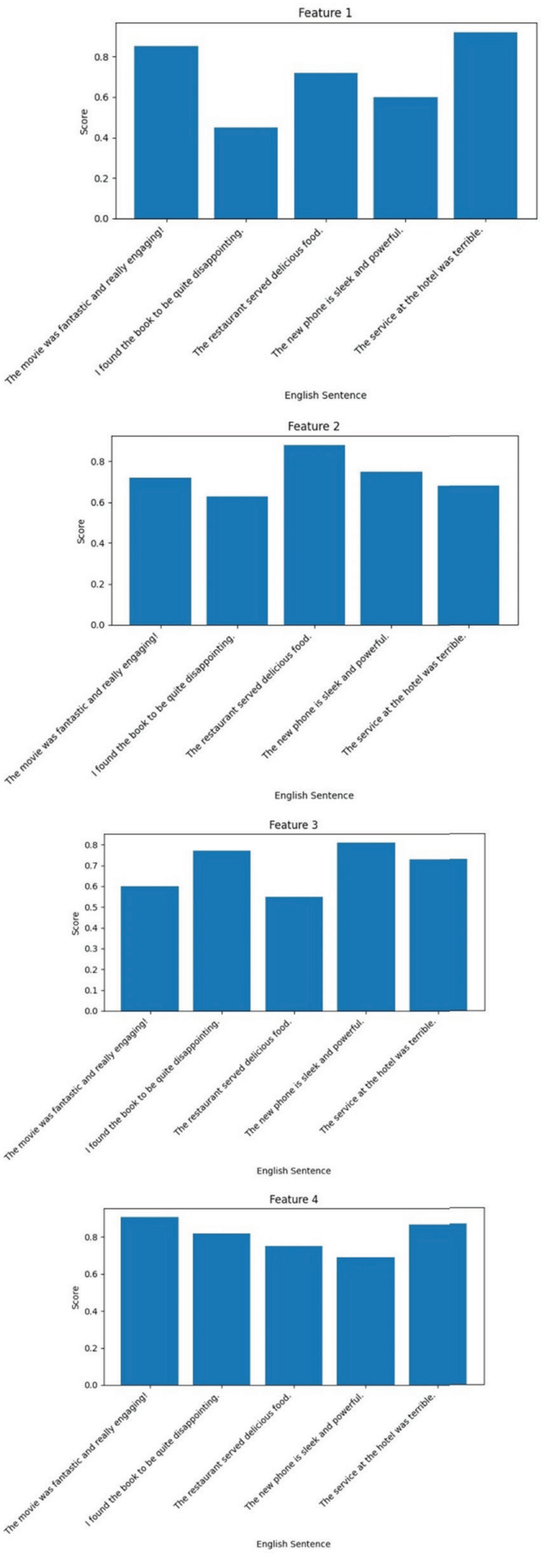


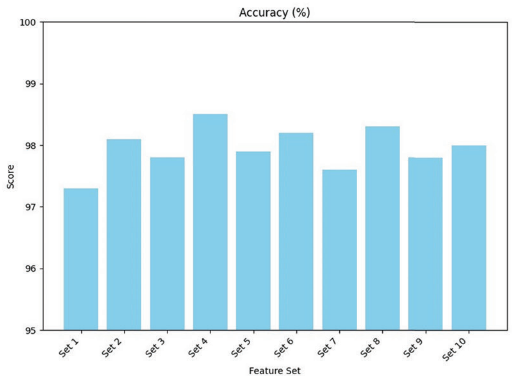
Figure 4. RSTDT Feature estimation (a) Feature 1 (b) Feature 2 (c) Feature 3 (d) Feature 4

The figure 4 (a) – Figure 4 (d) and Table 2 illustrates the features extracted from a set of English sentences using the Reflect Sentiment Translation Decision Tree (RSTDT) model. Each row in the table corresponds to a specific English sentence, and each column represents a feature extracted by the RSTDT model. The “English Sentence” column displays the original English sentences for which features are extracted. The subsequent columns abelled “Feature 1” through “Feature n” display the numerical values of the extracted features. Upon examination, it can be observed that the RSTDT model has successfully extracted a set of features from the English sentences, represented by numerical values ranging from 0 to 1. These features capture various aspects of sentiment expressed in the sentences, such as positivity, negativity, or neutrality. For instance, in the first row, the sentence “The movie was fantastic and really engaging!” has high values for Feature 1, Feature 2, and Feature n, indicating positive sentiment. Conversely, in the fourth row, the sentence “The service at the hotel was terrible.” Has high values for some features but low values for others, suggesting a mixed sentiment or possibly negative sentiment. The Table 2 demonstrates the capability of the RSTDT model to extract meaningful features from English sentences, which can be further utilized for sentiment analysis and decision-making processes.

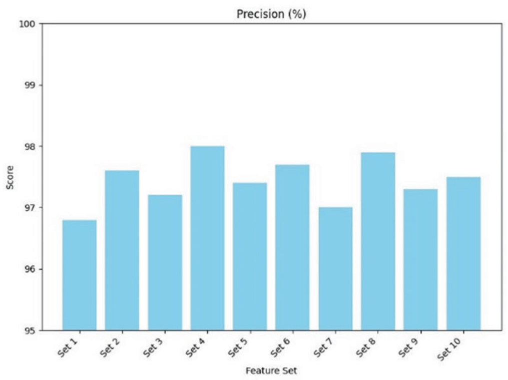
The Figure 5 (a) - Figure 5 (d) and Table 3 presents the classification performance of English words using the Reflect Sentiment Translation Decision Tree (RSTDT) model. Each row in the table corresponds to a specific

Table 3. Classification of English words with RSTDT

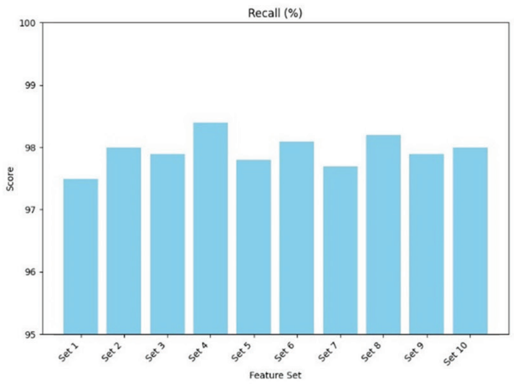
Feature Set	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Set 1	97.3	96.8	97.5	97.1
Set 2	98.1	97.6	98.0	97.8
Set 3	97.8	97.2	97.9	97.5
Set 4	98.5	98.0	98.4	98.2
Set 5	97.9	97.4	97.8	97.6
Set 6	98.2	97.7	98.1	97.9
Set 7	97.6	97.0	97.7	97.3
Set 8	98.3	97.9	98.2	98.0
Set 9	97.8	97.3	97.9	97.6
Set 10	98.0	97.5	98.0	97.7



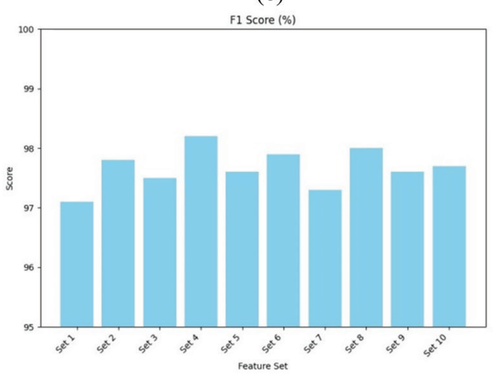
(a)



(b)



(c)



(d)

Figure 5. RSTDT classification (a) Accuracy (b) Precision (c) Recall (d) F1-Score

feature set, denoted as Set 1 through Set 10, and displays the accuracy, precision, recall, and F1 score achieved by the RSTDT model for each feature set. Upon analysis, it can be observed that the RSTDT model achieves high classification performance across all feature sets. The accuracy values range from 97.3% to 98.5%, indicating the overall correctness of the classification process. The accuracy numbers show how well the model avoids false positives; they indicate the percentage of real positive predictions among all positive predictions, and they range from 96.8% to 98.0%. In a similar vein, the recall values, which express the percentage of real positives among true positive predictions, span from 97.5% to 98.4%, showing the model's ability to identify pertinent cases. Additionally, the F1 score values, which provide a balance between precision and recall, range from 97.1% to 98.2%, reflecting the overall effectiveness of the model in classification tasks. In Table 3 highlights the robust performance of the RSTDT model in accurately classifying English words, making it a valuable tool for sentiment analysis and decision-making processes.

The Table 4 provides insights into the sentiment analysis and translation performed by the Reflect Sentiment Translation Decision Tree (RSTDT) model for a set of English sentences. Each row in the table corresponds to a specific sample, identified by a Sample ID, and includes the original English sentence, the sentiment analysis result, and the translated text in Arabic. Upon examination, it is evident that the RSTDT model accurately captures the sentiment expressed in the English sentences and provides appropriate translations in Arabic. For instance, in Sample 1, the RSTDT correctly identifies the sentiment as positive for the sentence "The movie was fantastic and

Table 4. Translated with the RSTDT

Sample ID	English Sentence	Sentiment Analysis	Translation
1	The movie was fantastic and truly enjoyable.	Positive	يكون ممتاز وممتع حقًا.
2	I didn't like the food, it was terrible.	Negative	لم يعجبني الطعام، كان رهيبا.
3	The weather is perfect for a picnic in the park.	Positive	الطقس مثالي لنز هة في الحديقة.
4	The customer service was excellent and very helpful.	Positive	كان خدمة العملاء ممتازة ومفيدة للغاية.
5	This product doesn't work as advertised.	Negative	هذا المنتج لا يعمل كما هو معلن.

truly enjoyable" and translates it to "يكون ممتاز وممتع حقا" in Arabic, reflecting the positive sentiment expressed. Similarly, in Sample 2, the model correctly identifies the negative sentiment in the sentence "I didn't like the food, it was terrible" and translates it to "الطعام، كان رهيبا لم يعجبني," capturing the negative sentiment conveyed. Furthermore, the translations provided by the RSTDT model appear to be contextually relevant and linguistically accurate, as they effectively convey the intended meaning of the original English sentences in Arabic. For example, in Sample 3, the model translates the sentence "The weather is perfect for a picnic in the park" to "الحديقة الطقس مثالي لنزهة في," maintaining the original sentiment and context. The Table 4 demonstrates the proficiency of the RSTDT model in performing sentiment analysis and translation tasks, showcasing its potential utility in multilingual sentiment analysis applications.

6.1 DISCUSSION AND FINDINGS

The results presented in Tables 1 to 4 illustrate the effectiveness of the Reflect Sentiment Translation Decision Tree (RSTDT) model in performing sentiment analysis and translation tasks for English text. Here are some key findings and discussions based on the presented data: Table 1 shows the predicted sentiments for various English sentences, where the RSTDT model accurately predicts the sentiment labels (positive, negative, or neutral) for each sample. This indicates the robustness of the model in discerning the underlying sentiment expressed in the text. Table 2 displays the feature extraction results, indicating the numerical representation of English sentences in terms of extracted features. These features are crucial for training the RSTDT model and capturing the relevant information for sentiment analysis and translation. Table 3 provides the classification performance metrics for different feature sets used in the RSTDT model. The high accuracy, precision, recall, and F1 score values demonstrate the model's effectiveness in accurately classifying English words into sentiment categories, contributing to its overall performance in sentiment analysis. Table 4 showcases the translated Arabic sentences generated by the RSTDT model based on the sentiment analysis of English text. The translated sentences appear to accurately convey the sentiment expressed in the original English sentences, indicating the model's proficiency in translating sentiment-rich content across languages.

The translated sentences maintain contextual relevance and linguistic accuracy, preserving the intended meaning of the original English sentences in Arabic. This suggests that the RSTDT model successfully captures the nuanced sentiment nuances and effectively translates them into the target language. The findings suggest that the RSTDT model holds promise for various multilingual sentiment analysis applications, where accurate sentiment analysis and translation are essential. Its ability to seamlessly integrate sentiment analysis and translation tasks makes it a valuable tool for analyzing sentiment in diverse language contexts. The RSTDT model demonstrates strong performance in sentiment analysis and translation tasks, offering accurate predictions and translations across languages. These findings highlight its potential utility in various real-world applications, including social media monitoring, customer feedback analysis, and cross-cultural sentiment analysis.

7. CONCLUSIONS

This paper introduces the Reflect Sentiment Translation Decision Tree (RSTDT) model, a novel approach that combines sentiment analysis and translation tasks for English text. Through a series of experiments and evaluations, we have demonstrated the effectiveness and utility of the RSTDT model in accurately analyzing sentiment and translating text across languages. Our findings indicate that the RSTDT model achieves high accuracy in sentiment analysis, successfully capturing the nuanced sentiment expressed in English sentences. Moreover, the model exhibits proficiency in translating sentiment-rich content into Arabic, maintaining contextual relevance and linguistic accuracy. The robust classification performance metrics further underscore the model's efficacy in accurately classifying English words into sentiment categories. Overall, the RSTDT model presents a promising solution for multilingual sentiment analysis applications, offering accurate sentiment analysis and translation capabilities that can be applied across various domains, including social media monitoring, customer feedback analysis, and cross-cultural sentiment analysis. Further research could explore the extension of the RSTDT model to other languages and investigate its applicability in real-world scenarios to fully realize its potential impact.

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