# EmoHopeSpeech: An Annotated Dataset of Emotions and Hope Speech in English and Arabic

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## Abstract

This research introduces a bilingual dataset comprising 27,456 entries for Arabic and 10,036 entries for English, annotated for emotions and hope speech, addressing the scarcity of multi-emotion datasets. The dataset provides comprehensive annotations capturing emotion intensity, complexity, and causes, alongside detailed classifications and subcategories for hope speech. To ensure annotation reliability, Fleiss' Kappa was employed, revealing 0.75–0.85 agreement among annotators for both Arabic and English. The evaluation metrics (micro-F1-Score = 0.67) obtained from the baseline AraBERT model validate the quality of the data annotations.

## 1 Introduction

In recent years, the proliferation of online content has emphasized the need for a deeper understanding of language and its impact on emotions and hope speech. The study of emotions in textual data has applications in various domains, including mental health monitoring (Dheeraj and Ramakrishnudu, 2021; Fei et al., 2020), customer sentiment analysis (Chintala, 2024), and personalized recommendations (Babanne et al., 2020). Similarly, hope speech, which refers to positive and uplifting expressions, plays a crucial role in promoting harmony, mitigating harmful narratives, and fostering inclusive communication (Balouchzahi et al., 2023). Also, identifying and promoting hope speech could help counter the spread of toxic content and support digital well-being.

Despite the significance of these areas, there remains a lack of comprehensive, multilingual datasets that cater to the analysis of both emotions and hope speech, particularly in underrepresented languages like Arabic. The inclusion of both English and Arabic in this dataset offers unique opportunities to explore cross-linguistic and cross-cultural comparisons in emotional expression and positivity. Arabic, as one of the most widely spoken languages globally, presents unique challenges and opportunities for emotion and hope speech detection due to its rich dialectal variations and complex morphological structure (Elnagar et al., 2021).

Coupled with English, which is widely studied in NLP, this paper introduces EmoHopeSpeech, a bilingual annotated corpus that focuses on emotions and hope speech in English and Arabic. The dataset paves the way for dual language and cross-cultural studies, enriching the global research landscape (Gutiérrez et al., 2016). The dataset is designed to capture the cultural and linguistic understandings of these two diverse languages. It includes labels for a variety of emotional categories and classifications for hope speech, providing researchers with a valuable resource to advance natural language processing (NLP) models in these domains. We describe the dataset's construction, annotation process, and key characteristics, demonstrating its potential for advancing research in natural language processing, sentiment analysis, and cross-cultural communication. This work not only addresses the need for balanced datasets in low-resourced languages but also fosters the development of more inclusive and culturally aware AI systems.

Our dataset comprises carefully curated social media posts in both English and Arabic, annotated in a new direction of emotion analysis which consists of basic emotions, emotion intensity, complexity of emotion, and emotion causes. We labeled hope speech into binary label, and granular categories. The annotation process involved native speakers of both languages and followed a rigorous methodology to ensure high-quality labels. This dual-language approach enables comparative analysis of emotional expression patterns and hope speech characteristics across different cultural and



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linguistic contexts. This paper makes several key contributions to the field of natural language processing and affective computing:

- The first large-scale dataset combining emotion and hope speech annotations in English and Arabic.
- A detailed analysis of annotation challenges and solutions specific to hope speech detection in multilingual contexts.
- Baseline models demonstrating the feasibility of joint emotion and hope speech detection.
- Insights into cross-cultural patterns of emotional expression and hope speech.

Our research establishes a foundation for developing NLP-based content analysis systems capable of identifying negative content requiring moderation, as well as positive, hope-inspiring content deserving amplification to foster healthier online environments. The remainder of this paper is organized as follows: Section 2 reviews related work in emotion detection and hope speech analysis. Section 3 describes the methodology for data collection, annotation, and preprocessing. Section 4 discusses the structure of the data set and statistical insights. Section 5 presents potential applications and evaluation results. Finally, Section 6 concludes with future research directions.

## 2 Related Works

A good number of work has been done in the English language for Emotion analysis. Emotion analysis tasks can be classified in two ways. First is a publicly available dataset that is annotated with emotion labels. Second is the approach to developing machine learning and deep learning techniques to classify text into emotion labels. While we discuss datasets, we need to comply with different categories: textual, voice, image, memes, and multimodal (image+text). Yang (Yang et al., 2023) collected 3 million images, out of which humans annotated 118,102 images and became the largest emotion dataset. Table 1 shows the recent work on emotion dataset.

Chakravarthi, 2020 developed a multilingual hope speech dataset of 6176 entries in English, Tamil, and Malayalam languages. Balouchzahi et al. 2023 collected English tweets and created a hope speech dataset. Divakaran et al. build a hope speech dataset from Reddit posts comprising of two languages Spanish and English. However, according to the best knowledge of the author, no hope speech work has been done in Arabic. We aimed to create a large scale hope speech dataset for hope speech. Moreover, the integration of emotion annotation with hope speech meaningful insight into public sentiment.

| Dataset | Modality | Annotation Label | Size | Language |
|---|---|---|---|---|
| EmoSet (Yang et al., 2023) | Image | 7 emotion label | 118,102 | English |
| Semval-2019 (Chatterjee et al., 2019) | Text | 3 emotion label | 38,424 | English |
| ISEAR (Scherer and Wallbott, 1994) | Text | 7 emotion label | 7,665 | English |
| CARER (Saravia et al., 2018) | Text | 8 emotion label | 2,000 | English |
| Arabic (Teahan, 2019) | Text | 7 emotion label | 1221 | Arabic |

Table 1: Summary of datasets with their modalities, annotation labels, sizes, and languages.

## 3 Data Collection and Annotation

### 3.1 Data Collection

We collected publicly available emotion datasets in Arabic and English that were labeled with basic emotion labels (happiness, sad, love, joy, amused, disgust, fear, empathy, and confidence). The root datasets belong to three different sources i) Arabic Poetry emotions(Shahriar et al., 2023), ii) Emotional Tone(Al-Khatib and El-Beltagy, 2018), iii) Multilabel Hate speech dataset(Zaghouani et al., 2024). The Arabic Poetry emotions dataset has 9452 rows, the Emotional Tone dataset has 10065 rows, and the Hate speech dataset has 30000 rows. In total, 49,517 Arabic data were labeled with emotions. We kept rows in which text data had more than 5 words and less than 80 words. After filtering out, 27,456 rows remain. To keep track of the original sources of data, we have added a column for sources that keeps the URL of the original data. The datasets contain both both Modern Standard Arabic (MSA) and dialectal arabic text.

For English dataset, we merged two existing datasets (Anjali, 2024; Saravia et al., 2018). We extended the dataset from basic emotion label to granular emotion labels and hope speech. After filtering with min and max words, it was left with 10036 rows for further analysis of the hope speech.

### 3.2 Bias Reduction

For both the Arabic and English datasets, we extend the basic emotion dataset to a deeper analysis of emotion and hope speech. To minimize bias in our Arabic and English tweet datasets, we implemented a comprehensive set of strategies. We ensured truly random sampling with stratified techniques to capture underrepresented groups, applied transparent and dialect-aware filtering criteria to preserve linguistic diversity, and harmonized merged English datasets to address inconsistencies. Diverse annotators with clear guidelines labeled granular emotions and hope speech, achieving high inter-annotator agreement. All processes, including sampling, filtering, and annotation, were thoroughly documented to ensure transparency and reproducibility.

### 3.3 Data Annotation Process

The dataset was initially labeled with the basic emotion label: happiness, sad, love, joy, amused, disgust, fear, empathy, anger, confidence. We employed five native Arabic speakers to annotate the Arabic dataset into different types of emotion labels (Emotion Intensity, Complexity of Emotion, and Emotion Cause) and hope speech labels. The native Arabic speakers are male and female from different Arab countries such as Qatar, Tunisia, Jordan, and Egypt, maintaining the diversity. It also ensures the dialectal variation of data annotation. A manager manages the data annotation process. There were several training sessions to train the annotators. Annotators meet frequently to discuss their progress and resolve conflicts through discussions. Similarly, for English data, five annotators were involved in this data annotation task. Guidelines were provided with proper examples, both in Arabic and English. Guidelines were revised several times to make them clear for understanding. Table 2 to Table 6 explain the data annotation guidelines with illustrated examples.

**Emotion Intensity:** Table 2 provides a structured framework to categorize the intensity of emotions expressed in both English and Arabic texts. It has four categories: Low, Medium, High, and Not Applicable. Annotator assess the intensity or strength of the emotion expressed in the text and select the label that best matches the emotional intensity.

| Label | Guidelines | English Example | Arabic Example |
|---|---|---|---|
| Low | The emotion is present but not strongly expressed | "I'm a bit worried about the test tomorrow, but it's not a big deal." | أنا قلق قليلاً بشأن الامتحان غدًا، لكن الأمر ليس مهمًا |
| Medium | The emotion is clear and noticeable but not overwhelming | "I'm worried about the test tomorrow; it's making me feel uneasy." | أنا قلق بشأن الامتحان غدًا؛ يجعلني أشعر بعدم الارتياح. |
| High | The emotion is intense and strongly expressed | "I'm extremely worried about the test tomorrow! I can't stop thinking about it, and it's driving me crazy!" | أنا قلق للغاية بشأن الامتحان غدًا! لا أستطيع التوقف عن التفكير فيه، إنه يجنني! |
| Not Applicable (N/A) | No emotion is present or intensity cannot be determined | "The test is scheduled for tomorrow." | الامتحان مجدول ليوم غد |

Table 2: Emotion Intensity Table

**Emotion Complexity**: The Table 3 framework demonstrates the complexity of emotion. There are four categories of emotion complexity: simple, medium, complex, N/A (Not Applicable). The task is to evaluate whether the emotion in the text is simple or complex.

**Emotion Cause:** The table 4 provides a framework for annotators to classify text based on what is causing the expressed emotion. It is used in sentiment analysis or emotion recognition tasks where understanding the cause is important.

**Hope Speech:** Hope Speech in Table 5 categorizes texts that express hope, positivity, encouragement, or a constructive outlook as "Hope Speech," differentiating them from "Not Hope Speech," which lacks these elements. The table also includes "Counter Speech," which challenges negativity or hate speech constructively, and "Neutral" texts, which are factual or devoid of emotional tone. Additionally, it defines "Hate Speech or Negativity" to capture texts that are offensive, harmful, or convey negative sentiments. The table provides examples in both English and Arabic to ensure clarity and applicability across languages, making it a valuable tool for annotating and analyzing multilingual datasets.

**Hope Speech Subcategories:** The table 6 categorizes hope speech into four distinct themes, each with its unique focus and purpose. Inspirational/Motivational emphasizes uplifting and motivating individuals, encouraging perseverance in

| Label | Guidelines | English Example | Arabic Example |
|---|---|---|---|
| Simple | The text clearly expresses a single, straightforward emotion. | I'm so happy today! | أنا سعيد جدًا اليوم |
| Medium | The emotion is more detailed than simple, but it's still easy to understand and not as complex as feeling several emotions at once. | I'm feeling a bit frustrated, but it's not too bad. | أشعر بالإحباط قليلاً، لكن الأمر ليس سيئًا للغاية |
| Complex | The text expresses multiple emotions or a nuanced emotional state. | I'm excited about the new job, but also nervous about leaving my old one. | أنا متحمس للعمل الجديد، لكنني أشعر بالتوتر أيضًا بشأن ترك عملي القديم |
| Not Applicable (N/A) | No clear emotion or complexity cannot be determined. | The meeting is scheduled for 3 PM. | الاجتماع مجدول في الساعة الثالثة مساءً |

Table 3: Complexity of Emotion Table

| Label | Guidelines | English Example | Arabic Example |
|---|---|---|---|
| External Event | Emotion is caused by an event or situation outside the individual. | I felt scared when I heard the loud thunderstorm outside. | شعرت بالخوف عندما سمعت العاصفة الرعدية القوية في الخارج |
| Internal Reflection | Emotion arises from internal thoughts or self-reflection. | I feel so guilty for the mistakes I've made in the past. | أشعر بالذنب الشديد بسبب الأخطاء التي ارتكبتها في الماضي |
| Relationship | Emotion is linked to interactions or relationships with others. | I was heartbroken when my friend stopped talking to me. | شعرت بالحزن الشديد عندما توقف صديقي عن الحديث معي |
| Achievement Or Failure | Emotion is related to personal success or failure. | I was overjoyed when I got the promotion at work. | كنت سعيدًا جدًا عندما حصلت على الترقية في العمل |
| Unclear | The cause of the emotion is not clear. | I've been feeling really down lately, but I don't know why. | أشعر بالاكتئاب في الفترة الأخيرة، لكن لا أعرف السبب |
| Not Applicable (N/A) | No clear emotion or cause is stated. | The project is due next week. | المشروع يجب أن يُسلم الأسبوع القادم |

Table 4: Emotion Cause Table

the face of challenges, as seen in messages about achieving the impossible with determination and persistence. Solidarity/Peace highlights unity, community support, collective action, and the promotion of peace. Lastly, Spiritual/Empowerment includes speech inspired by religious or spiritual beliefs.

## 4 Statistical Result

Table 7 provides a detailed comparison of emotional expressions in Arabic and English across three dimensions: Complexity of Emotion, Emotion Intensity, and Emotion Cause. For Complexity of Emotion, Arabic texts show a higher complexity of medium emotion (51.86%) compared to English (27%), but a lower proportion of simple emotions (23.98% vs. 54%), suggesting Arabic expressions are complex compare to Engish. In Emotion Intensity, Arabic texts exhibit a higher proportion of high-intensity emotions (38.19% vs. 30.14%) and a lower proportion of low-intensity emotions (12.21% vs. 19.14%), indicating stronger emotional expression in Arabic. For emotional cause, Arabic texts emphasize relationships (40.29%) and internal reflection (39.45%) whereas English (21.14% and 34.79%, respectively), while English texts more frequently cite external events (24.69% vs. 12.51%) and achievement/failure (9.83% vs. 4.07%). These differences highlight distinct cultural or linguistic tendencies in emotional expression, with Arabic favoring relational and intense emotions, and English showing greater diversity in external and achievement-related causes.

**Hope Speech Results:** Table 8 provides a detailed comparison of Hope Speech Categories and Hope Speech Subcategories across Arabic and English datasets, highlighting both the distribution and variation in proportions.

In the Hope Speech Categories, the "Neutral" category dominates in both Arabic (9,278, 34%) and English (1,894, 46%), indicating a significant presence of neutral expressions in the data. The "Hope Speech" category, which reflects positive and uplifting content, is more prevalent in Arabic (3,375, 12%) compared to English (574, 14%). Conversely, the "Negative/Hate Speech" and "Counter Speech" categories show lower proportions, with Arabic exhibiting a higher count (4,578, 16% and 1,178, 4%, respectively) than English (212, 5% and 38, 0.009%).

In the Hope Speech Subcategories, "Inspira-

| Label | Definition | Arabic Example | English Example |
|---|---|---|---|
| Hope Speech | Express hope, positivity, encouragement, or a constructive outlook. | ننجح في النهاية بغض النظر عن الصعوبات | We will succeed in the end despite the difficulties. |
| Not Hope Speech | Does not contain any elements of hope or positivity. | لا توجد تطورات جديدة | There are no new developments. |
| Counter Speech | Hate speech or negativity with the intention of refuting or challenging it. | يجب علينا أن نرفض كل أشكال الكراهية | We must reject all forms of hatred. |
| Neutral | Neutral or factual in nature, without conveying hope, positivity, or countering negative speech. | المؤتمر سيعقد غدًا في الساعة التاسعة صباحًا | The conference will be held tomorrow at 9 AM. |
| Hate Speech or Negativity | Offensive or harmful text, often targeting individuals or groups such as race, religion, ethnicity. | أمثالك هم السبب في كل المشاكل. يجب أن تشعر بالخجل | People like you are the cause of all the problems. You should be ashamed. |

Table 5: Categories of Hope Speech

| Label | Definition | Arabic Example | English Example |
|---|---|---|---|
| Inspiration | Inspire and motivate individuals and encourage them to keep going despite challenges. | العزيمة والإصرار، يمكننا تحقيق المستحيل | With determination and persistence, we can achieve the impossible. |
| Solidarity | Emphasizes community support, collective action, and promotion of peace and reconciliation | بالتعاون بيننا، سنتمكن من تجاوز كل العقبات | Through our cooperation, we will overcome all obstacles. |
| Resilience | Focuses on the resilience of individuals or communities and the long-term vision for a better future | نحن نبني مستقبلًا مشرقًا لأجيالنا القادمة | We are building a bright future for the next generations. |
| Spiritual | Religious or spiritual beliefs to instill hope. | لكل واحد منا القدرة على تغيير واقعه للأفضل | Each one of us has the power to change our reality for the better. |

Table 6: Subcategories of Hope Speech

tional/Motivational" dominates in both languages, accounting for 39% in Arabic (1,270) and 48% in English (279). Subcategories like "Spiritual Em-

| Category | Arabic (N) (%) | English (N) (%) |
|---|---|---|
| **Complexity of Emotion** | | |
| Medium | 13173 (0.51) | 2734 (0.27) |
| Complex | 6138 (0.24) | 1744 (0.17) |
| Simple | 6090 (0.23) | 5468 (0.54) |
| **Emotion Intensity** | | |
| Medium | 12602 (0.49) | 5062 (0.50) |
| High | 9700 (0.38) | 3008 (0.3) |
| Low | 3101 (0.12) | 1910 (0.19) |
| **Emotion Cause** | | |
| Internal Reflection | 10024 (0.39) | 3475 (0.34) |
| Relationship | 10238 (0.40) | 2111 (0.21) |
| External Event | 3180 (0.12) | 2465 (0.24) |
| Achievement/Failure | 1033 (0.04) | 982 (0.9) |
| Unclear | 934 (0.03) | 954 (0.9) |

Table 7: Summary of Complexity of Emotion, Emotion Intensity, and Emotion Cause by Language

powerment" and "Solidarity/Peace" show similar trends, although Arabic has higher counts overall. Notably, "Resilience/Visionary" is represented proportionally higher in English (20%) compared to Arabic (16%).

| Category | Arabic (N) (%) | English (N) (%) |
|---|---|---|
| **Hope Speech Categories** | | |
| Neutral | 9278 (0.34) | 5265 (0.46) |
| Hope Speech | 3375 (0.12) | 1496 (0.14) |
| Not Hope Speech | 9043 (0.33) | 2993 (0.32) |
| Hate Speech | 4578 (0.16) | 244 (0.05) |
| Counter Speech | 1178 (0.04) | 38 (0.009) |
| **Hope Speech Subcategories** | | |
| Inspirational | 1270 (0.39) | 1188 (0.48) |
| Spiritual | 864 (0.26) | 132 (0.16) |
| Solidarity | 543 (0.17) | 83 (0.14) |
| Resilience | 539 (0.16) | 94 (0.2) |

Table 8: Summary of Hope Speech Categories and Subcategories by Language

## 5 Data Analysis

### 5.1 Corelation between Emotion and Hope Speech:

Table 9 summarizes the results of chi-square tests between different emotional characteristics—such as Emotion Intensity(EI), Complexity of Emotion (CM), Emotion Cause(EC) and categories of hope speech (HS), Hope Speech Subcategories(HSC) examined in both Arabic and English texts. It includes the chi-square statistics and corresponding p-values for each comparison. In particular, all relationships show statistically significant results ($p \leq 0.05$), with many having p values of 0, reflecting very strong significance. The chi-square values vary across the comparisons, indicating different levels of association. The correlation between emotion labels and hope speech categories stands out with the highest chi-square values for Arabic (1502.6) and English (160.5), highlighting the strongest association observed.

| Relationship | Arabic ($\chi^2$, P-Value) | English ($\chi^2$, P-Value) |
|---|---|---|
| EI vs. HC | 324.3, 0 | 194.7, 0 |
| EI vs. HSC | 72.9, 0 | 16, 0.004 |
| CM vs. HS | 354.3, 0 | 56.3, 0 |
| CM vs. HSC | 40.7, 0 | 43.1, 0 |
| EC vs. HC | 810.3, 0 | 245.6, 0 |
| EC vs. HSC | 121.3, 0 | 88.4, 0 |

Table 9: Corelation between Emotion and Hope Speech

### 5.2 Dataset Evaluation

We analyzed the dataset annotations using both traditional machine learning methods, such as logistic regression and multinomial Naive Bayes, alongside modern transformer-based models like BERT. The preprocessing workflow included steps such as tokenization, cleaning the text, and transforming it into formats ready for modeling. To improve data quality, we eliminated stopwords from both Arabic and English datasets. For the Arabic dataset, we relied on the stopword list provided by (Alrefaie, 2019), and for the English dataset, we used tools from the NLTK library.

We fine-tuned AraBERT (Antoun et al., 2020), a pre-trained transformer model designed specifically for Arabic natural language processing tasks, and BERT-based-uncased (Devlin et al., 2018) for the English dataset. Both models were trained on the Hope Speech dataset to classify categories, using their language-specific optimizations and contextual embeddings to improve prediction accuracy. Table 10 shows the model evaluation metrics in our annotated dataset and provides a well-rounded assessment of the effectiveness of the models aligned with the annotated labels.

| Hope Speech Prediction - Arabic Data | | | | |
|---|---|---|---|---|
| Model | Precision | Recall | F1-Score | Accuracy |
| LR | 0.53 | 0.55 | 0.52 | 0.55 |
| AraBERT | 0.69 | 0.69 | 0.67 | 0.69 |
| NB | 0.54 | 0.55 | 0.51 | 0.55 |
| **Hope Speech Prediction - English Data** | | | | |
| LR | 0.50 | 0.54 | 0.59 | 0.44 |
| AraBERT | 0.64 | 0.69 | 0.64 | 0.69 |
| NB | 0.49 | 0.53 | 0.52 | 0.53 |

Table 10: Evaluation Metrics for Hope Speech Data

## 6 Error Analysis

We provided a sample of 1000 instances to all annotators and instructed them to annotate the data. Since multiple annotators were involved and the label are categorical, we calculated Fleiss' Kappa scores to measure the level of agreement. Table 11 shows that Arabic data are generally higher than those of English, reflecting better consistency among annotators for Arabic annotations. The highest agreement was for the "Emotion Cause" label in Arabic (0.81), which means annotators often agreed on what caused the emotion. Good agreement was also seen for "Complexity of Emotion" (0.77 in Arabic, 0.79 in English) and "Emotion Intensity" (0.75 in Arabic, 0.74 in English), showing that annotators had a shared understanding of how strong or complex the emotions were.

| Label | Arabic | English |
|---|---|---|
| Emotion Intensity | 0.75 | 0.74 |
| Complexity of Emotion | 0.77 | 0.79 |
| Emotion Cause | 0.81 | 0.72 |
| Hope Speech Categories | 0.71 | 0.75 |
| Hope Speech Subcategories | 0.65 | 0.61 |

Table 11: Inter-Annotator Agreement Fleiss' Kappa

## 7 Conclusion and Future Work

This study introduced a bilingual dataset in Arabic and English that combines annotations for both emotions and hope speech. By extending existing datasets with additional layers such as emotion intensity, complexity, causes, and hope speech subcategories, the dataset offers rich, multi-dimensional data for analyzing emotional and positive language in diverse contexts. Baseline models, including AraBERT and BERT, showed promising results in detecting hope speech categories, confirming the usefulness of the dataset for prediction tasks.

## Ethics and Impact

This study addresses the ethical and societal implications of creating Arabic and English emotion and hope-speech datasets and models. Guided by fairness, inclusivity, and cultural sensitivity, we cite original sources, include no personal identifiers (IRB-exempt), and employ diverse annotators with clear guidelines to minimize bias, inconsistency, and harm—especially in hate and counter-speech contexts.

## Dataset Release

The user can freely access this dataset by filling in a consent form: https://forms.gle/S9fZtYjAyLAqFsH19 mentioning that the data can only be used for academic or research purposes.

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