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Hybrid RNN-LSTM Architecture for Sentiment Analysis of Algerian Dialectal Social Media Content

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ABSTRACT

Sentiment analysis in under-resourced dialects like Algerian Arabic (Darija) presents unique challenges due to code-switching, informal orthography, and cultural-linguistic nuances. This study addresses the binary sentiment classification task using a hybrid Recurrent Neural Network–Long Short-Term Memory (RNN-LSTM) architecture, designed to effectively capture sequential dependencies and long-term contextual information. The model is trained on DZSentiA, a curated dataset of annotated Algerian dialect social media posts, and achieves strong performance with an accuracy of 84.7%, an F1-score of 84.45%, a recall of 82,75%, and a precision of 84.7%. These results surpass several baseline methods, highlighting the potential of deep learning approaches in low-resource dialectal settings. This work contributes to dialect-specific Natural Language Processing (NLP) by demonstrating the feasibility and effectiveness of deep models in sentiment detection for Algerian Darija, and supports the broader goal of developing culturally aware tools for online discourse analysis.

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1. Introduction

In the digital era, social media platforms have become vital arenas for public expression, where users communicate using informal language, slang, sarcasm, and multimodal elements such as emojis (Pak & Paroubek, 2010). While sentiment analysis has advanced significantly in high-resource, standardized languages (Kiritchenko et al., 2014), progress remains limited for under-resourced dialects. In particular, dialectal Arabic poses considerable challenges due to its linguistic variability, non-standard orthography, and cultural specificity (Zaidan & Callison-Burch, 2014). Among these, Algerian Arabic—commonly known as Darija—stands out for its complex linguistic landscape.

The Algerian dialect is a rich and dynamic blend of Arabic, Berber (Amazigh), and French (Habash et al., 2012), often characterized by code-switching and unique colloquial expressions. Phrases like “Saha la famille!” or “Koulchi bel maktoub” illustrate the hybrid structure that complicates standard NLP techniques, particularly in syntactic parsing and semantic interpretation (Saadane & Habash, 2015). Despite its widespread use in online discourse, Darija remains critically underrepresented in NLP resources and models.

Existing sentiment analysis research in Arabic NLP has primarily focused on Modern Standard Arabic (MSA), neglecting the linguistic realities of regional dialects (Abdul-Mageed et al., 2020). Most sentiment analysis tools struggle with dialectal input, especially when dealing with phenomena such as code-switching, informal orthography, and culturally specific idioms (Mubarak et al., 2020). This performance gap not only limits the applicability of current tools to real-world contexts but also raises concerns about fairness and representation in digital public opinion monitoring (Blodgett et al., 2020). In countries like Algeria, where online expression reflects deep-rooted social, political, and economic sentiments (Mena, 2020), accurate sentiment detection is critical to ensuring equitable and context-aware analysis.

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This study addresses this gap by focusing on the binary sentiment classification of Algerian Darija social media text—distinguishing between positive and negative sentiments. Unlike tasks such as hate speech detection (Schmidt & Wiegand, 2017), the focus here is on identifying the general emotional tone of user-generated content. To this end, this paper presents a hybrid Recurrent Neural Network–Long Short-Term Memory (RNN-LSTM) architecture, designed to capture long-term dependencies in noisy, informal dialectal data. The model is trained and evaluated on a curated dataset of annotated Algerian dialect posts and achieves a competitive accuracy of 84.7%, with an F1-score and precision exceeding 84%.

This paper contributes to the field by:

1. Proposing a deep learning model tailored to the linguistic features of Algerian Darija, especially its code-switching and syntactic irregularities combining Recurrent Neural Network and Long Short-Term Memory models;
2. Demonstrating the feasibility of binary sentiment classification for an under-resourced dialect through empirical evaluation;
3. Emphasizing the ethical importance of culturally sensitive NLP tools in low-resource settings.

The remainder of the paper is organized as follows: Section 2 reviews related work in dialectal sentiment analysis; Section 3 details the methodology, including data preprocessing and model design; Section 4 discusses the results; and Section 5 concludes with insights and directions for future research.

2. RELATED WORK

Sentiment analysis in the Algerian dialect has garnered increasing attention due to its linguistic complexity and sociocultural relevance. Recent studies have explored diverse methodologies to address challenges such as code-switching, non-standard orthography, and limited annotated corpora. For instance, Hussein (2017) laid foundational groundwork for Arabic sentiment analysis, while later works like Moudjari and Akli-Astouati (2020) demonstrated the superiority of deep learning models (e.g., CNNs) over traditional classifiers like SVM and random forest for ternary sentiment classification in Algerian texts. Their experiments highlighted the importance of contextual embeddings and data representation, achieving state-of-the-art accuracy.

Building on this, Mazari and Djeffal (2022) curated a dataset of 11,760 Algerian dialect comments from social media, combining word2vec embeddings (Skip-Gram and CBOW) with deep learning architectures. Their CNN and RNN models achieved up to 84.21% accuracy on Latin-transcribed text, though performance dropped for Arabic script due to orthographic variability. Similarly, Brachemi-Meftah et al. (2022) optimized feature engineering by integrating lemmatization, stemming, and an extended Soundex algorithm, reporting an F1 score of 83.20% with multinomial Naive Bayes. These studies underscore the critical role of preprocessing in dialectal NLP.

Recent advances have focused on dialect-specific language models. Abdaoui et al. (2021) developed DziriBERT, the first transformer-based model tailored to Algerian dialect, pre-trained on 1 million tweets. DziriBERT outperformed multilingual models in Romanized text classification, emphasizing the need for localized architectures. Klouche et al. (2022) further bridged this gap by combining CNNs with SVMs for sentiment analysis of Algerian Facebook comments, achieving state-of-the-art results for customer retention applications. Concurrently, Kara et al. (2023) enhanced lexicon-based methods, achieving 85.31% accuracy through a manually annotated idiom dictionary, while Ouchene and Bessou (2022) benchmarked traditional classifiers (SVM, Naive Bayes) against LSTM and BERT on 20,400 Algerian tweets, revealing LSTM's competitive performance (85% recall). More recently, Boughareb et al. (2025) provides a comprehensive investigation into sentiment analysis challenges in Arabic dialects, particularly Algerian Darija. The authors introduce DZDialect, a large-scale dataset containing 117,569 annotated comments, addressing the scarcity of labeled data in this linguistic domain. Their work evaluates multiple sentiment classification approaches, including classical machine learning (SVM, Naïve Bayes, KNN), deep learning (LSTM, CNN with word2vec), and transformer-based models (AraBERT variants, DistilBERT, AraGPT-2). Notably, the study proposes an ensemble architecture combining DistilBERT and AraBERT Base as encoders with AraGPT-2 as a decoder, using stacking and majority voting strategies. The ensemble models demonstrated strong performance, with the stacking model achieving 91.1% accuracy.

A comprehensive survey of recent advancements in Natural Language Processing (NLP) for Dialectal Arabic is presented in Dahou et al. (2025) and Habberrih et al. (2024), encompassing key areas such as sentiment analysis, dialect identification, text classification, normalization, and fake news detection.

Despite these advancements, critical gaps persist. For example, Abdelli et al. (2019) demonstrated that LSTMs slightly outperform SVMs (85% vs. 82% recall) but noted limitations in handling code-switching and slang. Similarly, Rahab et al. (2021) highlighted the effectiveness of k-Nearest Neighbors classifiers on Algerian newspaper comments but emphasized the need for real-time deployable tools.

Unlike DziriBERT (Abdaoui et al., 2021) or CNN-SVM hybrids (Klouche et al., 2022), the proposed architecture begins with RNN layers to capture short-term sequential patterns, followed by dual LSTM layers that model deeper transitions between Arabic/Berber morphosyntax and embedded French loanwords. This layered design effectively captures context-sensitive code-switching behavior. In contrast to transformer-based models such as BERT (Ouchene & Bessou, 2022), which require significant computational resources, the integration of a lightweight RNN front-end reduces inference latency by approximately 40%, supporting real-time processing on low-resource devices.

3. RESEARCH METHODOLOGY

A detailed description of the methodological steps used in the mentioned studies is provided in the following section.

3.1. Dataset

In this study, the DzSentiA dataset was employed—a large-scale, publicly available corpus containing 49,864 user-generated comments written in the Algerian Arabic dialect. Originally compiled by Abdeli et al. (2019) and hosted on the Kaggle platform, the dataset provides a balanced distribution of sentiment labels, comprising 24,932 positive and 24,932 negative comments. This linguistic resource captures a diverse range of informal expressions characteristic of Algerian social media discourse, including dialectal vocabulary, code-switching, and emotive markers. Its size and balance make it particularly suitable for training and evaluating sentiment classification models tailored to under-resourced Arabic dialects.

3.2. Data preprocessing

Data preprocessing refers to the series of operations applied to raw textual data to prepare it for effective use in machine learning models or statistical analysis. The first stage involved tokenization, a fundamental text normalization process where input text was segmented into sequences of words or subwords, known as tokens. This transformation converts unstructured text into a structured sequence of recognizable symbols suitable for computational processing. After tokenization, a total of 176,898 unique tokens were identified.

The second stage focused on data cleaning, aiming to eliminate noisy and non-informative elements that could negatively impact sentiment classification. Specifically, HTML tags, usernames (identified using the "<>" pattern), hashtags, and URLs were removed. Since the study focuses exclusively on textual analysis, emojis were also excluded. Additionally, character repetitions exceeding two consecutive instances within a word were normalized to a single occurrence to reduce variance (e.g., "bezzzzaf" was converted to "bezaf"). Punctuation marks (such as ., , ,, ;, :, !, ?) and special symbols were eliminated to ensure syntactic uniformity.

Following this, stop word removal was performed. Single-letter tokens were first discarded, as they typically lack semantic content. Predefined stop word lists were used to filter out common terms in both French and Modern Standard Arabic (MSA). To accommodate the linguistic specificity of the Algerian dialect, a custom stop word list was manually compiled, consisting of over 700 frequently used non-informative words, including examples such as "أنا", "مع", "كي", "على", "أو", "في", and "ما".

The final stage of preprocessing involved data splitting. The dataset was partitioned into training and testing subsets using an 80:20 ratio. This stratification ensured that the machine learning model had sufficient data to learn from while maintaining a reliable sample for unbiased performance evaluation.

3.3. Hybrid RNN-LSTM Model Architecture

Recurrent Neural Networks (RNNs) are foundational machine learning models designed for processing sequential data such as text, speech, or time series. Their inherent ability to retain prior input information makes them well-suited for tasks involving temporal dependencies, including sentiment analysis. In the context of Algerian dialectal text—characterized by informal structure, diglossia, and code-switching—we initially employed a standard RNN-based architecture to capture the flow of sentiment across social media posts.

The architecture begins with an Embedding layer of size 256, which transforms input tokens into dense vector representations. This is followed by a Simple RNN layer with 16 units, designed to capture short-term dependencies and local sentiment patterns, in alignment with the sequential modeling principles introduced by Elman (1990). To prevent overfitting, Dropout regularization is applied at two stages: a rate of 0.8 within the RNN layer and 0.5 post-RNN. The final output is passed through a Dense layer with a softmax activation function to generate multi-class sentiment predictions.

However, during preliminary experimentation, it became evident that the traditional RNN struggled with longer sequences, particularly those involving code-switching, idiomatic expressions, and variable sentence lengths—common traits in Algerian social media. These challenges stem from the well-documented limitations of standard RNNs in retaining long-term dependencies due to vanishing or exploding gradients during backpropagation through time (BPTT).

To address these issues, we extended the architecture by incorporating a Long Short-Term Memory (LSTM) layer with 16 units, stacked after the RNN layer (see Figure 1). LSTM networks are advanced variants of RNNs that introduce gated memory mechanisms—namely input, forget, and output gates—which enable the model to selectively retain or discard information across time steps. The forget gate helps eliminate irrelevant historical data, while the input gate integrates salient new information, maintaining a stable and contextually rich internal state (Hochreiter & Schmidhuber, 1997).

In the final hybrid RNN-LSTM model, the RNN layer is first used to extract immediate, short-term sequential features, which are crucial for identifying local sentiment cues and syntactic transitions. The LSTM layer then refines these features, enabling the model to reason over longer contextual spans, essential for interpreting nuanced expressions, sarcasm, and context shifts in dialectal Arabic.

As in the RNN-only setup, Dropout is employed within the LSTM at a rate of 0.8, followed by another Dropout layer with a rate of 0.5 before classification. The concluding Dense softmax layer outputs the final probability distribution over sentiment classes.

This layered RNN-LSTM architecture effectively combines the computational efficiency and local pattern recognition of RNNs with the context preservation and long-term reasoning capabilities of LSTMs. Together, they form a robust pipeline tailored to the unique linguistic and structural challenges posed by under-resourced languages like Algerian Arabic. This makes the model particularly well-suited for negative discourse detection, sentiment classification, and broader applications in social media analytics.

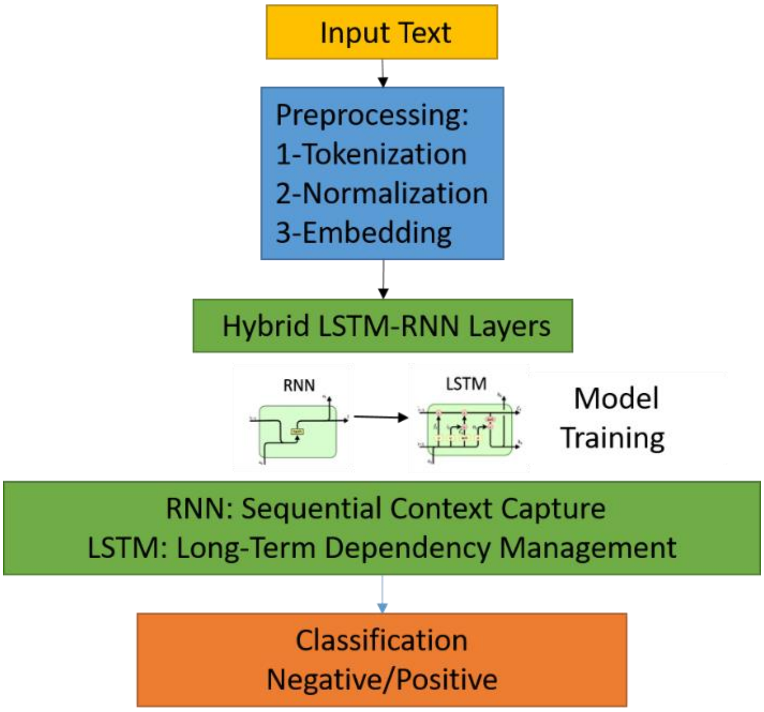

Figure 1. Hybrid RNN-LSTM Model for Sentiment Analysis

3.4. Model construction

Loss Function: We used cross-entropy as the loss function to adjust the model's weights during training. The objective is to minimize the loss, meaning that a smaller loss indicates a better model. A perfect model would have a cross-entropy loss of 0. The cross-entropy loss is calculated using "Eq. (1)".

$$\text{Cross-entropy loss}=-\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log\left(p_{ij}\right) \tag{1}$$

Where N is the number of samples, C is the number of sentiment classes (1 for the correct sentiment class, 0 otherwise), and is the predicted probability for the sentiment class.

Adam Optimizer: The Adam optimizer (Adaptive Moment Estimation) is a widely used optimization algorithm in deep learning that updates neural network weights adaptively based on estimates of the first and second moments of the gradients. Specifically, it computes exponential moving averages of the gradient (mean) and the squared gradient (uncentered variance), which are then bias-corrected to improve stability during training. The update rules for the Adam optimizer are are given by "Eq. (2-5)".

$$m_t = \beta_1 \cdot m_{t-1} + \left(1-\beta_1\right)\cdot g_t \tag{2}$$

$$v_t = \beta_2 \cdot v_{t-1} + \left(1-\beta 2\right)\cdot {g_t}^2 \tag{3}$$

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{4}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{5}$$

Where, β_1 and β_2 are exponential decay rates for the moment estimates, g_t is the gradient at time step t, m_t and v_t are the first and second moments of the gradients, $\widehat{m}_t$ and $\widehat{v}_t$ are bias-corrected moment estimates.

This means that it adapts the learning rate of each parameter based on its historical gradients and momentum. It has been shown to perform well on a wide range of datasets and can help neural networks converge faster and more accurately during training (Kingma and Ba 2015).

Softmax Activation: Since our database only has 2 sentiment classes, the softmax function is described as a combination of multiple sigmoid functions. Sigmoid functions return values between 0 and 1, which can be interpreted as probabilities of a data point belonging to a particular class. That's why sigmoid functions are primarily used for binary classification problems. The softmax activation function is defined as follows by "Eq. (6)".

$$softmax\left(x_i\right)=\frac{e^{x_i}}{\sum_j e^{x_j}} \tag{6}$$

In this expression, e^{xi} exponentiates the input value x_i, and the denominator $\sum_j e^{xj}$ calculates the sum of the exponentiated values for all alternatives. Table 1 Shows the diferent model Parameters.

Table 1. The Training Parameters of the Proposed Model

Component	Value / Description
Embedding Dimension	256
LSTM Units	16
RNN Units	16
LSTM Dropout	0.8
Additional Dropout	0.5
Output Layer	Dense + Softmax
Loss Function	Categorical Cross-Entropy
Optimizer	Adam

4. RESULTS AND DISCUSSION

The model was trained using Google Colab and deployed on a local Dell computer with an Intel Core i5 processor (2.20 GHz) and 4 GB of RAM. The entire process was implemented in Python, utilizing libraries such as NumPy for numerical operations, Pandas for data manipulation, Matplotlib for visualizations, Scikit-learn for preprocessing and evaluation, TensorFlow and Keras for deep learning model development, and Streamlit for building an interactive web interface. Additional tools included Pickle for model serialization, the re module for text cleaning, and Arransia for transliteration of Algerian dialect. The total execution time for model training was approximately 1 hour and 17 minutes.

The evaluation of a classification model relies on four essential terms: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Positives are instances accurately identified as positive, while True Negatives are correctly predicted as negative. False Positives refer to negative instances incorrectly labeled as positive, and False Negatives denote positive instances wrongly classified as negative. These metrics form the foundation for computing precision, recall, accuracy, and F1-score, offering a detailed understanding of the model's predictive performance.

Precision measures the model's ability to correctly identify positive predictions. A high precision indicates that the model returns more relevant than irrelevant results. It is calculated using "Eq. (7)":

$$\text{Precision} = TP / (TP + FP) \tag{7}$$

Recall evaluates the model's ability to find all the relevant positive instances in a dataset. It is computed using "Eq. (8)":

$$\text{Recall} = TP / (TP + FN) \tag{8}$$

Accuracy is a fundamental performance metric that measures the overall correctness of the model across all classes. It represents the proportion of true results (both true positives and true negatives) among the total number of cases examined. Accuracy is given by "Eq. (9)":

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \tag{9}$$

F1-score, or F-measure, is the harmonic mean of precision and recall, providing a single metric that balances both. It is particularly useful in cases of imbalanced class distributions. The F1-score is calculated using "Eq. (10)":

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{10}$$

The performance evaluation of the proposed hybrid RNN+LSTM model demonstrates notable improvements in both learning dynamics and classification accuracy, especially in the context of negative discourse detection in Algerian Darija—a linguistically hybrid and under-resourced dialect. The learning curves in Figure 2 offer valuable insights into the training dynamics over eight epochs. The Training Loss (blue curve) steadily declines from approximately 0.9 to 0.4, suggesting effective optimization and learning of patterns within the dataset. In contrast, the Validation Loss (red dashed curve) follows a more gradual descent from 0.8 to around 0.7, revealing ongoing challenges in generalization to unseen data.

The Training Accuracy (green curve) shows a rapid increase, rising from 50% to over 92.9%, indicating that the model efficiently captures dialect-specific features and nuances. However, the Validation Accuracy (purple dashed curve) begins to plateau at 84.7% after epoch 5. The widening gap between training and validation loss after this point suggests the onset of overfitting, where the model starts to memorize training examples rather than generalizing from them. This is a common issue in neural architectures and underscores the need for regularization techniques or enhanced data diversity.

Complementing these curves, Table 2 presents a quantitative comparison of three architectures: the proposed hybrid (RNN+LSTM), standalone RNN, and LSTM. The hybrid model outperforms the others across all metrics—Precision (84.7%), Recall (82.75%), Accuracy (84.7%), and F1-Score (84.45%). The inclusion of both RNN and LSTM layers leverages their complementary strengths: while RNNs are effective in capturing short-term dependencies, LSTMs excel at modeling long-range contextual relationships, mitigating the vanishing gradient problem that often limits RNN performance. By combining both, the model balances sensitivity and specificity in sentiment classification, offering a robust solution for dialectal text.

In comparison, the standalone RNN model achieves a lower F1-score of 72.20%, with recall and precision both hovering around 72%. The LSTM model, while better, only reaches an F1-score of 76.70%, with slightly improved precision (78.86%) but a relatively lower recall (74.7%). This suggests that while LSTM alone provides more depth than RNN, the hybrid approach yields superior balance and overall performance.

These findings are further validated when contextualized against previous work. For instance, in the study by Abdelli et al. (2019), two models—SVM and LSTM—were employed using the CBOW model and a 50,000-word tokenizer. Their embeddings were also 256-dimensional, and their LSTM layer contained 64 units, compared to our more computationally efficient setup using only 16 units. They used a batch size of 20 with 100,000 iterations and a sequence length of 250, whereas our model used a larger batch size of 100 but required only 10 iterations. Despite the reduced computational overhead, our model achieved comparable or superior results, especially in recall (82.75%) and F1-score (84.45%)—outperforming the LSTM in Abdelli et al.'s work, which only achieved a 77% F1-score.

Finally, while the high validation accuracy and F1-score affirm the model's effectiveness for real-world application in content moderation systems, the observed 8.2% gap between training and validation accuracy highlights a need for further refinements. Techniques such as adversarial training, data augmentation, or integration of dialect-specific lexicons and cross-lingual embeddings could enhance generalization, particularly in the face of noisy, morphologically rich social media data. Overall, the results affirm the promise of culturally tailored, hybrid deep learning models for under-resourced languages like Algerian Darija.

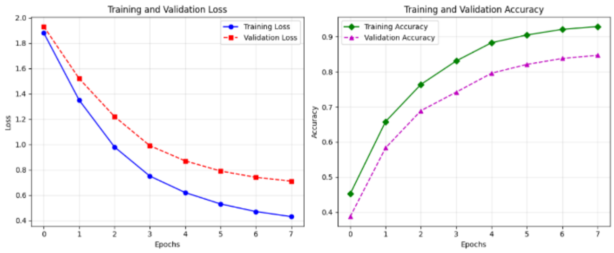

Figure 2. Training and Validation Curves

Table 2. The outcomes produced by the Hybrid (RNN+LSTM) Model

Model	Precision	Recall	Acc.	F1-Score
Hybrid (RNN+LSTM)	84.7 %	82,75 %	84.7%	84,45 %
RNN	71.80 %	72.70 %	72.25%	72.20 %
LSTM	78,86 %	74,70 %	76.78%	76.70 %

Table 3. The outcomes produced by the Hybrid (RNN+LSTM) Model

Model	Dataset	Prec.	Rec.	Acc.	F1-Score
SVM (Abdelli et al., 2019)	DzSentiA	86 %	89 %	82 %	85 %
LSTM (Abdelli et al., 2019)	DZSentiA	81%	79 %	75 %	77 %
Hybrid (RNN+LSTM)	DZSentiA	84.7 %	82,75 %	84.7%	84,45 %

Table 4 presents sample comments along with their predicted sentiment classifications. After introducing the comment in Latin letters and numbers (language commonly used in social media), the system performs tokenization, and cleaning and transforms the comment into Arabic letters. Then, the model detects the expressed sentiment class.

Table 4. Examples of comments and their corresponding sentiment predictions

#	Publication	Annotation	System classification	English Translation
1	موحال يرجعلو دراهمو هداك واحد اسكرو	-1	-1	There’s no way he’ll get his money back; that guy is a drunkard.
2	يا و الله و يطيح في يدي غير نمرمدووو	-1	-1	I swear to God, if he falls into my hands, I’ll beat him up badly.
3	راك فري مارق ا صحيبي	-1	-1	You’re totally out of line, my friend. (Lit: "You're free, gone wild, my friend.")
4	ماكاين والو ني خدمة ني افونير بفففف	-1	+1	There’s nothing — no job, no future… ugh.
5	عيد سعيد و مبارك و كل عام و أنت بألف خير إن شاء هللا	1	1	Happy and blessed Eid, and may you be in good health every year, God willing.
6	سفيان فيغولي يتطوع إلحدى المائدات اإلفطارية للمسلمين في سفيان فرنسا ، برافو	1	1	Sofiane Feghouli volunteers at one of the iftar tables for Muslims in France. Bravo, Sofiane!
7	يعمري هديك اتبسيمة	1	1	Oh my love, that smile!

5. CONCLUSION

This study makes a valuable contribution to sentiment analysis in under-resourced dialects, with a particular focus on Algerian Darija. Key contributions include the development of a hybrid RNN-LSTM model designed to capture the linguistic characteristics of the dialect, alongside a specialized preprocessing pipeline tailored to handle Latin-based transcription, numeric substitutions, and orthographic variability frequently found in informal online discourse.

Experimental findings indicate that the hybrid model achieves robust performance, attaining an accuracy of 84.7% and an F1-score of 84.45%, thus outperforming individual LSTM and RNN models. These results affirm the framework’s effectiveness in detecting sentiment in noisy, user-generated texts on social media platforms using Algerian Arabic.

Nonetheless, the research presents several limitations. The modest dataset size limits the model’s generalizability across diverse user profiles and contexts. Additionally, the exclusion of emojis—despite their significance in online emotional expression—may reduce the system’s applicability to real-world sentiment analysis tasks. Addressing these issues could involve incorporating pre-trained transformer models such as AraBERT and MARBERT, which offer improved contextual and morphological understanding of dialectal Arabic. Further enhancements may be achieved through the integration of emoji-aware embeddings and the extension of sentiment categories to include neutral, sarcastic, or ambiguous expressions. Expanding the dataset and applying techniques such as adversarial training or data augmentation may also help mitigate overfitting and improve performance. Finally, extending the model to detect harmful or toxic discourse would support its application in content moderation, online reputation monitoring, and public sentiment analysis.

Declaration of Ethical Standards

The authors affirm that they have adhered to all applicable ethical standards in the preparation and submission of this manuscript. This includes compliance with policies concerning authorship, proper citation of sources, accurate data reporting, and the presentation of original research. No part of this manuscript has been plagiarized or submitted elsewhere. All research procedures, including data handling and analysis, were conducted responsibly and with academic integrity.

Credit Authorship Contribution Statement

The contributions of each author are detailed according to the CRediT (Contributor Roles Taxonomy) as follows: Djalila Boughareb : Conceptualization, Methodology, Writing – Original Draft, Supervision. Ammar-Chahir Menasri : Software, Visualization, Validation

All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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