SmolLab_SEU at MAHED 2025: Do Arabic-Native Encoders Surpass Multilingual Models in Detecting the Nuances of Hope, Hate, and Emotion?

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Abstract

The dynamic interplay of hope and hate speech on Arabic social media presents a critical challenge for content moderation and digital discourse analysis. This paper presents our systems for the MAHED 2025 shared task on Multimodal Detection of Hope and Hate Emotions in Arabic Content, addressing the two text-based subtasks. Our approach centers on a systematic, empirical comparison of Arabic-native versus large-scale multilingual Transformer encoders to determine the optimal pre-training strategy for this nuanced domain. Comprehensive evaluations demonstrate the clear superiority of Arabic-native models, with our ARBERTv2-based system achieving the highest performance. We secured 11th place in Subtask 1 with a macro F1-score of 0.682 and 5th place in Subtask 2 with a macro F1-score of 0.514. Error analysis reveals persistent challenges in interpreting implicit language and overcoming severe class imbalance, particularly in distinguishing targeted hate from general offensiveness. This work contributes a robust benchmark for this comparison and underscores the importance of language-specific pre-training for nuanced affective computing in Arabic.

1 Introduction

The proliferation of social media has transformed the Arabic-speaking world into a complex information ecosystem where constructive and destructive narratives compete. This duality is starkly represented by the concurrent rise of hate speech and hope speech, making their automatic detection paramount for content moderation and understanding online discourse (Mubarak et al., 2017). While early Arabic NLP efforts focused on general sentiment, the community has shifted towards more nuanced, high-impact tasks like hate speech detection.

The advent of large pre-trained Transformers (Devlin et al., 2019) has revolutionized this field, becoming the de facto standard. However, a fundamental architectural question remains for Arabic: do exclusively pre-trained Arabic-native models offer a performance advantage over large-scale multilingual models like XLM-RoBERTa (Ruder et al., 2019)? The latter may offer broader linguistic generalization, while the former might better capture language-specific nuances, dialects, and cultural contexts.

The MAHED 2025 shared task at ArabicNLP 2025 (Zaghouani et al., 2025) provides an ideal testbed to investigate this question. Its focus on the duality of hope and hate speech, alongside a complex emotion classification challenge, pushes beyond simple toxicity detection. In this paper, we present our systems for Subtask 1 and 2, systematically evaluating a diverse suite of Arabic-native and multilingual Transformer models to empirically answer this question.

The main contributions of our work:

- We developed Transformer-based systems for both subtasks, including a cascaded pipeline that models hierarchical label dependencies in Subtask 2.
- We empirically compared Arabic-native and multilingual encoders, demonstrating the superiority of language-specific models and providing an error analysis that highlights failures due to semantic nuance and class imbalance.

2 Related Works

The automatic detection of nuanced affective states, including hate and hope speech, is a critical area of research in Arabic Natural Language Processing (NLP). Our work builds upon recent advancements in deep learning for sentiment and emotion analysis, particularly those leveraging Transformer-based architectures.

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Recent efforts in Arabic affective computing highlight the success of pre-trained models. For instance, Cherrat et al. (2024) demonstrated the efficacy of AraBERT-based models for sentiment analysis across Standard Arabic and Moroccan dialect, showcasing their ability to capture complex linguistic features. Similarly, for Arabic tweet classification, Al-Onazi et al. (2023) developed a framework combining Deep Belief Networks with advanced hyperparameter optimization, while Elfaik et al. (2023) engineered a feature-fusion model using hybrid RNN-CNN architectures to tackle multi-label affect analysis. These studies affirm the power of deep learning for Arabic text but often focus on general sentiment or a broad spectrum of emotions.

This trend of applying sophisticated deep learning models extends to other languages and related tasks. Researchers have employed CNNs for detecting violent incitement in Urdu (Khan et al., 2024), hierarchical attention networks for depression detection from English tweets (Khafaga et al., 2023), and various hybrid architectures for emotion classification in Afan Oromo (Abdella and Sori, 2024). Furthermore, the field is advancing towards more complex methodologies, such as the tri-modal (text, audio, visual) graph neural networks for emotion recognition proposed by Al-Saadawi and Das (2024).

Building on this foundation, our work addresses the MAHED 2025 task by providing a direct, empirical comparison between Arabic-native and multilingual Transformer encoders. The complex nature of detecting not only *hate* but also *hope* and associated emotions serves as a valuable testbed for evaluating how these distinct pre-training strategies generalize to the nuances of Arabic social media content.

3 Task and Dataset Description

We participated in the MAHED 2025 shared task on the Multimodal Detection of Hope and Hate Emotions in Arabic Content, hosted at the ArabicNLP 2025 workshop. The task aimed to advance the automatic detection of hate speech, hope speech, and associated emotions in Arabic text. Our work addresses the two text-based subtasks: Subtask 1 and Subtask 2. The official performance metric for both subtasks was the macro-averaged F1-score.

Subtask 1, Text-based Hate and Hope Speech Classification, required systems to perform a three-way classification of Arabic text into hate, hope, or not_applicable.

Split	Instances	Unique Words	Total Words
Train	6,890	62,744	147,285
Validation	1,476	17,553	30,731
Test	1,477	17,891	31,492

Table 1: Dataset statistics for Subtask 1.

Split	Instances	Unique Words	Total Words
Train	5,960	45,015	115,279
Validation	1,277	13,726	25,346
Test	1,278	13,339	24,596

Table 2: Dataset statistics for Subtask 2.

Subtask 2, Emotion, Offensive Language, and Hate Detection, was a multi-output classification challenge. The goal was to simultaneously predict the associated Emotion (from 12 labels), determine if the content was Offensive (binary), and, if so, classify its Hate content (binary).

The shared task provided two distinct datasets (Zaghouani et al., 2024; Biswas and Zaghouani, 2025a,b), one for each subtask, with dedicated training, validation, and test splits. The datasets consist of Arabic text from various online sources, reflecting both Modern Standard Arabic (MSA) and dialectal variations. Tables 1 and 2 provide detailed statistics for each dataset.

4 Methodology

Our approach involves fine-tuning both multilingual and Arabic-native Transformer models (Vaswani et al., 2017), which excel at capturing the contextual cues necessary for nuanced hate and hope speech detection. We employed distinct strategies for the Hate and Hope Speech Classification (Figure 1) and the Emotion, Offensive, and Hate Detection (Figure 2) subtasks.

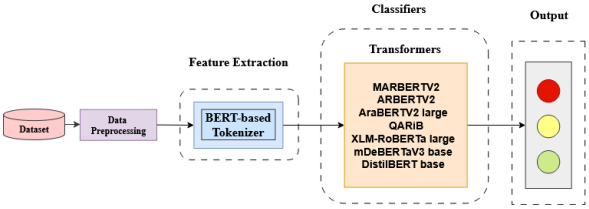

Figure 1: Schematic process for Hate and Hope Speech Classification.

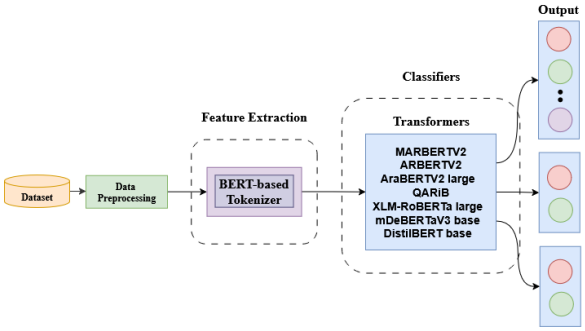

Figure 2: Schematic process for motion, Offensive, and Hate Detection.

4.1 Data Preprocessing

We implemented a unified text normalization pipeline for both subtasks prior to model-specific tokenization. The pipeline systematically removed URLs, user mentions, and hashtags, then normalized whitespace and filtered out non-Arabic characters. The cleaned text was subsequently processed using the AutoTokenizer corresponding to each pre-trained model. All input sequences were either padded or truncated to a fixed maximum length, generating `input_ids` and `attention_mask` tensors for model consumption.

4.2 Transformer-Based Models

Our selection of encoders was designed to evaluate a diverse range of pre-training objectives and linguistic specializations. Our model suite included Arabic-native encoders such as MARBERTV2 (Abdul-Mageed et al., 2021), ARBERTV2 (Abdul-Mageed et al., 2021), AraBERTV2 large (Antoun et al.), and QARiB (Abdelali et al., 2021). These were complemented by powerful multilingual models, including XLM-RoBERTa large (Ruder et al., 2019), mDeBERTaV3 base (He et al., 2021), and the computationally efficient DistilBERT base (Sanh et al., 2019). Each model was adapted for the downstream tasks as described below.

For Subtask 1, framed as a standard sequence classification problem, we fine-tuned each Transformer encoder by appending a sequence classification head. This head comprises a linear layer that takes the final hidden-state representation of the [CLS] token as input to produce logits for the three target classes. The entire fine-tuning process was managed using the Hugging Face Trainer API (Wolf et al., 2020), which optimized a standard Cross-Entropy Loss function. To prevent overfitting, we integrated an `EarlyStoppingCallback`, configured to monitor the macro F1-score on the official validation set and halt training after 3 epochs without improvement. The model checkpoint yielding the highest validation F1-score was preserved for the final test set evaluation.

In contrast, for Subtask 2, we addressed the task's explicit hierarchical dependency by designing a cascaded pipeline of three independently optimized classifiers. This modular design avoids the potential negative interference of joint multi-task optimization and allows each model to specialize. The pipeline consists of: an Emotion Classifier (12-class), an Offensive Classifier (binary), and a Hate Classifier (binary). The Hate classifier was trained exclusively on the subset of training data labeled as Offensive. During inference, test instances are processed in parallel by the Emotion and Offensive models; instances classified as Offensive are then routed to the Hate classifier for the final prediction. Each model in this pipeline was fine-tuned using a custom PyTorch loop, employing a class-weighted Cross-Entropy Loss to counteract severe label imbalance. Model selection for each of the three components was based on the highest macro F1-score achieved on the validation dataset.

All experiments were conducted with the AdamW optimizer (Loshchilov and Hutter, 2017) and utilized mixed-precision (FP16) training for computational efficiency. The specific hyperparameters for all models are detailed in Table 3.

Model	LR	WD	BS	EP
Subtask 1: Hate and Hope Classification				
MARBERTV2	2e-5	0.01	32	10
ARBERTV2	2e-5	0.01	32	10
AraBERTV2 large	1e-5	0.01	32	7
QARiB	2e-5	0.01	32	10
XLM-RoBERTa large	2e-5	0.01	16	10
mDeBERTaV3 base	2e-5	0.01	16	10
DistilBERT base	2e-5	0.01	16	10
Subtask 2: Emotion, Offensive, Hate				
MARBERTV2	2e-5	-	16	8
ARBERTV2	2e-5	-	16	8
bert-base-arabertv2	2e-5	-	16	8
QARiB	2e-5	-	16	8
XLM-RoBERTa large	2e-5	-	16	8
mDeBERTaV3 base	2e-5	-	16	8
DistilBERT base	2e-5	-	16	8

Table 3: Hyperparameters used for fine-tuning. LR: Learning Rate, WD: Weight Decay, BS: Per-device Batch Size, EP: Max Epochs.

5 Result Analysis

This section presents the performance of our Transformer-based models on the MAHED 2025 shared task. All models were evaluated using the

official metrics: macro-averaged accuracy, precision, recall, and F1-score, with the macro F1-score serving as the primary metric for comparison. The comprehensive results for both subtasks are detailed in Table 4.

Model	Accuracy	Precision	Recall	F1 Score
Subtask 1: Hate and Hope Speech Classification				
MARBERTv2	0.6804	**0.6824**	0.6562	0.6665
ARBERTv2	**0.6879**	0.6794	**0.6939**	**0.6824**
AraBERTv2 large	0.6269	0.6547	0.5714	0.5802
QARiB	0.6770	0.6664	0.6831	0.6738
XLM-RoBERTa large	0.6567	0.6514	0.6652	0.6554
mDeBERTaV3 base	0.6798	0.6716	0.6794	0.6729
DistilBERT base	0.6330	0.6258	0.6124	0.6110
Subtask 2: Emotion, Offensive, and Hate Detection				
MARBERTv2	0.7272	0.5040	0.5163	0.5078
ARBERTv2	0.7089	**0.5316**	**0.5257**	**0.5142**
AraBERTv2 large	0.6922	0.4765	0.4575	0.4593
QARiB	**0.7415**	0.5259	0.4943	0.4915
XLM-RoBERTa large	0.6896	0.4609	0.4564	0.4506
mDeBERTaV3 base	0.6907	0.4498	0.4619	0.4504
DistilBERT base	0.6468	0.3761	0.3801	0.3749

Table 4: Performance comparison of all evaluated models for Subtask 1 and Subtask 2. The best score in each column is highlighted in **bold**.

In Subtask 1, the Arabic-native models demonstrated a clear advantage over their multilingual counterparts. ARBERTv2 emerged as the top-performing system, achieving the highest macro F1-score of 0.6824 and the best accuracy of 0.6879. This strong performance is likely attributable to its pre-training on a large corpus of Arabic social media and web data, which aligns closely with the task's domain. Notably, MARBERTv2 secured the highest precision at 0.6824, indicating its proficiency in correctly identifying positive instances, albeit with a slightly lower overall F1-score. Other Arabic-specific models like QARiB and the multilingual mDeBERTaV3 base also delivered competitive results, underscoring the effectiveness of modern Transformer architectures. Conversely, AraBERTv2 large and DistilBERT base lagged behind, suggesting that either model scale or pre-training objective was less suited to this specific classification challenge.

For the more complex, multi-output Subtask 2, ARBERTv2 once again demonstrated superior performance, leading across all macro-F1 (0.5142), precision (0.5316), and recall (0.5257) metrics. Its consistent success across both subtasks highlights the model's robustness and its ability to generalize well to related but distinct classification problems. MARBERTv2 followed closely with an F1-score of 0.5078. An interesting observation is the performance of QARiB, which achieved the highest accuracy (0.7415) but a lower F1-score of 0.4915. This discrepancy suggests the model may have excelled at predicting the majority classes (e.g., neutral emotion, no offensive) but struggled with the less frequent, yet critical, minority classes, reinforcing the importance of the macro F1-score as the primary evaluation metric in imbalanced scenarios.

Overall, our results indicate a distinct performance advantage for Arabic-native models pre-trained on diverse, user-generated content for both hate/hope speech detection and nuanced emotion classification. The performance gap between the two subtasks, with F1-scores being considerably lower in Subtask 2, underscores the inherent difficulty of the multi-output, hierarchically-dependent classification challenge. A detailed error analysis is provided in Appendix A.

6 Conclusion

In this paper, we presented our systems for the MAHED 2025 shared task, systematically evaluating Arabic-native and multilingual Transformer models on hope, hate, and emotion detection. Our findings consistently demonstrate the superiority of Arabic-native encoders, with our ARBERTv2-based system achieving a macro F1-score of 0.682 (11th place) in Subtask 1 and 0.514 (5th place) in the more complex Subtask 2. Despite these competitive results, our study is constrained by several limitations. Severe class imbalance, particularly in Subtask 2, led to a conservative bias and a high number of false negatives for the minority hate class. Our models also struggled with semantic nuance, often misclassifying subtle expressions of hope as neutral and confusing strong negative sentiment with targeted hate speech. Furthermore, the dataset may not fully capture the evolving nature of coded language across diverse Arabic dialects, and our work was confined to the text modality. Ultimately, this work contributes a robust benchmark comparing model architectures, affirming that language-specific pre-training remains crucial for tackling the subtleties of affective computing in Arabic.

Acknowledgments

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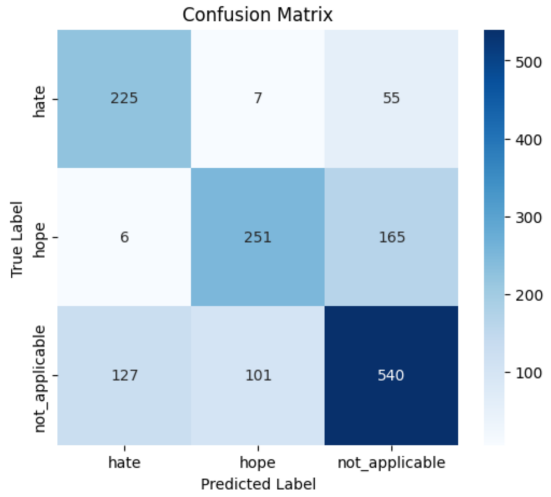
A Error Analysis

We conducted a quantitative and qualitative error analysis of our best model, ARBERTv2, on the test set to understand its performance and limitations.

A.1 Quantitative Analysis

For Subtask 1, Figure 3 reveals key performance patterns. The model performs well on the `not_applicable` (540 true positives), `hope` (251), and `hate` (225) classes. However, it struggles with nuance, misclassifying 165 `hope` instances as `not_applicable`. Additionally, it misclassifies 127 `not_applicable` cases as `hate`, suggesting an oversensitivity to strong negative language.



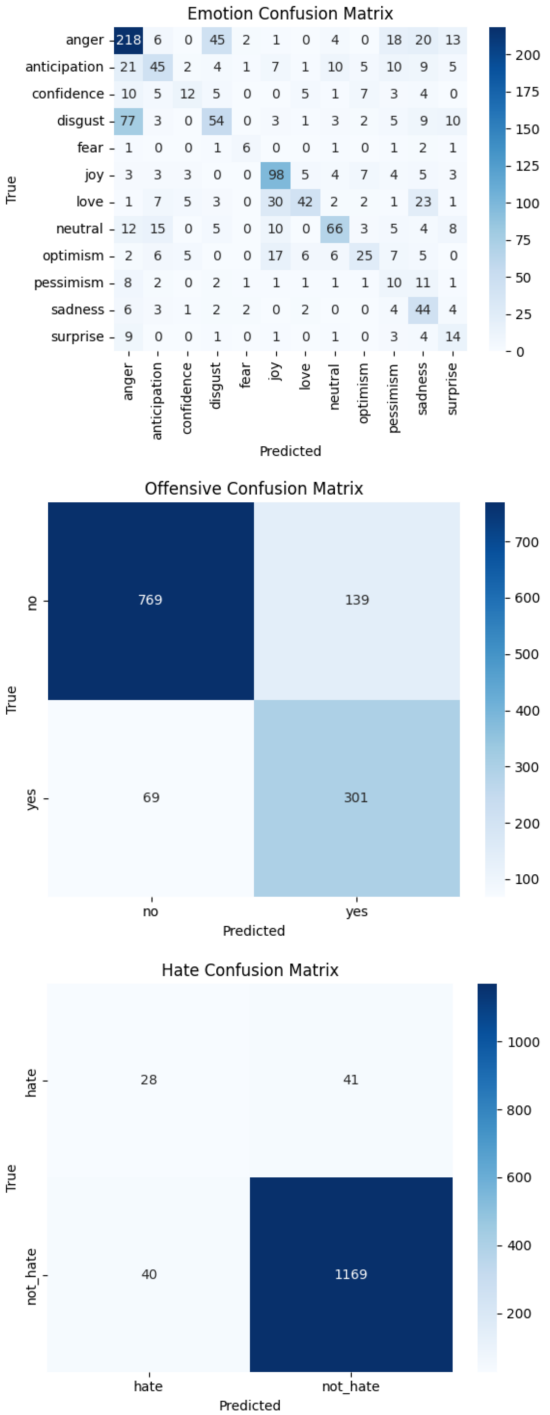
Subtask 1

Figure 3: Confusion matrix of the proposed model (ARBERTv2) for Hate and Hope Speech Classification.

For Subtask 2, Figure 4 shows the challenges at each stage of our cascaded pipeline. In **Emotion Detection**, the model excels at high-frequency classes like `anger` (218) and `joy` (98) but struggles with fine-grained distinctions, often confusing `optimism` with `neutral` (25) or `joy` (17). In **Offensive Detection**, the model shows a conservative bias, missing 139 offensive instances (false negatives) while correctly identifying 301. Finally, severe data imbalance in the **Hate Detection** stage heavily impacts performance; the model misclassifies 41 hate cases as `not_hate` while correctly identifying only 28, showing its difficulty in distinguishing targeted hate from general offensiveness.

A.2 Qualitative Analysis

Qualitative analysis of misclassifications reveals further limitations of ARBERTv2. For Subtask 1 (Figure 5), a politically charged text implying hostility was misclassified as `not_applicable` instead of `hate`, highlighting the model's difficulty with implicit threats that lack explicit slurs. For Subtask 2 (Figure 6), a text containing an expletive was mislabeled as `neutral` instead of `anger`. The



Subtask 2

Figure 4: Confusion matrices of the proposed model (ARBERTv2) for Emotion, Offensive, and Hate Detection.

formal phrasing seemingly overrode the informal expletive, highlighting challenges with mixed-tone sentences.

These observations confirm the system's primary weaknesses: handling nuanced language, distinguishing related emotions, and overcoming data imbalance, especially for targeted hate speech detection.

Subtask 1

Text Sample	Actual	Predicted
ترا شعور مرعب (What a terrifying feeling)	not_applicable	not_applicable
ينشبك حلمك بحلمي. (May your dream intertwine with my dream)	hope	hope
هنحاكم السيسي لانه كمم الافواه : (We will judge/prosecute Sisi because he silenced the mouths/voices.)	hate	not_applicable

Figure 5: Few examples of predictions produced by the proposed ARBERTv2 model on Subtask 1.

Subtask 2

Text Sample	Actual	Predicted
انا لحبيبي و حبيبي ألي (I belong to my beloved, and my beloved belongs to me.)	love,no,	love,no,
عدى خمس شهور انت متخيل؟ (Five months have passed, can you imagine?)	surprise,no,	surprise,no,
الجدير بالذكر أنه كسم #فارن (It is noteworthy that it's bullshit #Varane.)	anger,yes,not_hate	neutral,yes,not_hate

Figure 6: Few examples of predictions produced by the proposed ARBERTv2 model on Subtask 2.