Syntaxa at BAREC Shared Task 2025: BERTnParse - Fusion of BERT and Dependency Graphs for Readability Prediction

Ahmed Bahloul
School of Computation, Information and Technology, Technical University of Munich
Munich, Germany
ahmed.bahloul@tum.de

Abstract

We describe our system submission to **Task 1 (Sentence-level Readability Assessment)** of the BAREC Shared Task 2025 (Elmadani et al., 2025a), in the **strict track**. Task 1 requires predicting the readability level of an Arabic sentence on a scale from 1 (easiest) to 19 (hardest), reflecting reading difficulty. Our approach integrates contextual and syntactic information by combining pretrained BERT embeddings (Devlin et al., 2019) with a Graph Neural Network (GNN) (Zhou et al., 2021) over dependency parse trees (Kipf and Welling, 2017). Our hypothesis is that readability is influenced not only by word choice but also by syntactic complexity—especially in morphologically rich languages like Arabic (Habash, 2010). To capture both aspects, we represent each sentence as a dependency graph with BERT token embeddings as node features, and use a GNN to model the syntactic structure. Experimental results show that our syntax-aware model improves over a strong BERT baseline, highlighting the value of structural linguistic information for fine-grained readability classification.[1]

1 Introduction

Readability assessment aims to estimate the difficulty of a text for a given audience. For Arabic, this task is particularly challenging due to the language's rich morphology, flexible word order, and cliticization. Sentence-level readability prediction demands models that capture subtle syntactic and semantic cues. While transformer-based models like AraBERTv2 (Antoun et al., 2020) encode deep lexical features, they often underutilize syntactic structure—an important aspect of textual complexity.

We propose a hybrid architecture that integrates *syntactic dependency graphs* with *contextual embeddings* from AraBERTv2 for Arabic sentence-level readability prediction. Dependency trees are parsed into graphs and processed with a Graph Neural Network (GNN), while token embeddings from AraBERTv2 are used to represent semantic content. The resulting model jointly reasons over both syntactic and contextual signals.

While GNNs have been combined with transformers in tasks like QA (Yasunaga et al., 2021), document classification (Zhang et al., 2020), and semantic role labeling (Marcheggiani and Titov, 2017), such architectures have not been applied to **readability assessment**. For Arabic, prior work relies on feature-based or PLM-only methods (Liberato et al., 2024) or on word-level readability tools (Hazim et al., 2022; Al Khalil et al., 2020), rather than sentence-level prediction. Recent multilingual efforts such as ReadMe++ (Naous et al., 2024) evaluate both supervised and prompting-based methods, as well as unsupervised approaches, but all rely solely on pretrained language models without incorporating syntactic structure. This leaves the impact of syntax underexplored—especially in morphologically rich languages. The closest related work is by Ivanov (Ivanov, 2022), who compares syntax-based GNNs using fastText embeddings and BERT-based models for sentence complexity in Russian, but does not integrate syntactic and contextual representations into a unified model.

In addition to our architecture, we propose a novel alignment strategy that merges AraBERT subword embeddings and dependency parse nodes into **word-level units**. This is crucial for Arabic, where clitics and morphology lead to tokenization mismatches. Prior work often sidesteps this mismatch by propagating labels across subwords, but we instead ensure structural and semantic alignment through node merging and embedding pooling, enabling effective message passing in the graph.

Contributions: (1) We propose a syntax-aware model that fuses GNN-based syntactic representa-

[1]Code available at: https://github.com/ahmedehabb/BERTnParse

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Level	Arabic	Transliteration (HSB)	English
6	هنا يلتقي ماجد كل أسبوع بأصدقائه	hnA yltqy mAjd kl Âsbwς bÂSdqAŷh	Here Majid meets his friends every week.
11	ما هو المقصود دول عدم الانحياز؟	mA hw AlmqSwd dwl ςdm AlAnHyAz?	What is meant by the Non-Aligned Movement?

Table 1: Example BAREC sentences with readability levels, CAMeL Tools HSB transliterations, and English glosses.

tions with AraBERTv2 for Arabic sentence-level readability. (2) We introduce a word-level alignment method addressing tokenization mismatches between BERT and dependency parses. (3) We improve over a strong BERT baseline on the BAREC corpus (Elmadani et al., 2025b), especially for complex sentences.

2 Data

We evaluate our approach on the **Balanced Arabic Readability Evaluation Corpus (BAREC)** (Elmadani et al., 2025b), released as part of the BAREC Shared Task 2025. The dataset comprises Arabic sentences labeled with **19 readability levels** (1 = easiest, 19 = hardest), covering diverse topics and genres.

The dataset is split as follows:

- **Train set**: 54,845 sentences
- **Dev set**: 7,310 sentences
- **Test set**: 7,286 sentences
- **Blind Test set**: 3,420 sentences

Each sentence is annotated with a readability level following detailed linguistic and pedagogical guidelines (Habash et al., 2025). To illustrate the dataset, we provide examples with their readability levels, CAMeL Tools HSB transliterations (Habash et al., 2007), and English glosses.[2] Table 1 shows two representative examples.

Additional Arabic readability resources, such as the SAMER corpus (Alhafni et al., 2024), may be useful for future research. However, in line with the **strict track** guidelines of the BAREC Shared Task—where models must be trained exclusively on the BAREC training set—we restrict our experiments to the BAREC dataset only.

[2]Transliteration via the CAMeL Tools CLI: `camel_transliterate -s ar2hsb < file`

3 Methodology

Our approach combines contextual embeddings from AraBERTv2 (Antoun et al., 2020) with a Graph Neural Network (GNN) applied to the syntactic dependency graph of each input sentence. This design enables the model to jointly capture lexical semantics and syntactic structure, addressing key challenges in fine-grained Arabic readability prediction.

3.1 Input Representation

Given an input Arabic sentence $S = (w_1, w_2, \ldots, w_n)$, we first obtain token-level contextual embeddings $\mathbf{h}_i^{\text{BERT}} \in \mathbb{R}^d$ from AraBERTv2, where d is the embedding dimension. AraBERTv2 parameters are **fine-tuned** during training to adapt to the readability task.

Simultaneously, we parse S using CamelParser2.0 (Elshabrawy et al., 2023) to obtain a dependency graph $G = (V, E)$, where $V = \{w_i\}$ are nodes corresponding to tokens, and edges $E \subseteq V \times V$ represent syntactic relations. Each node $w_i \in V$ is also associated with a part-of-speech (POS) tag, and each edge $e = (w_i \to w_j) \in E$ is labeled with a dependency type (e.g., `OBJ`, `SUBJ`).

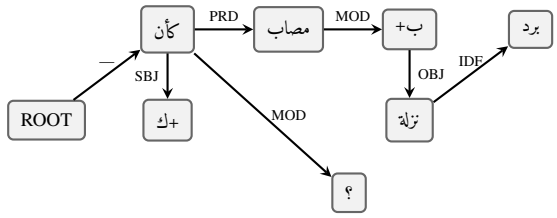
3.2 Token Alignment and Word-Level Processing

A key design decision in our system is to operate at the *word level* rather than on subword units. While AraBERTv2 employs WordPiece tokenization (Wu et al., 2016), which splits words into subword segments, the dependency parser outputs nodes that often correspond to grammatical morphemes or clitics. For example, the Arabic word سأصيدهما (transliteration: sÂSydhmA, translation: "I will catch them") is segmented into the future tense particle +س (s+, PART), the verb stem أصيد (Aṣyd, VRB), and the object pronoun suffix +هما (+hmA, NOM). This linguistically motivated segmentation differs from the subword units generated by BERT,

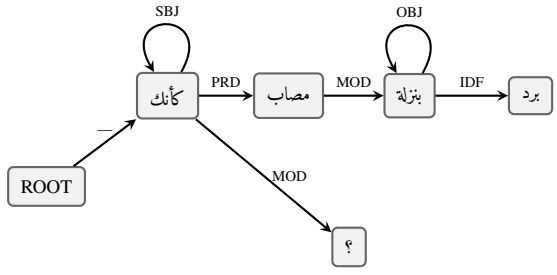
which are learned based on frequency statistics.

To resolve this mismatch, we average the AraBERTv2 subword embeddings into a single word-level vector, following the general idea of leveraging subword information for richer word representations (Bojanowski et al., 2017). On the parsing side, we merge subword nodes (e.g., clitics) and their associated edges into unified word-level graph nodes. This ensures that each word is consistently represented by both a single graph node and a single embedding. Figure 1 illustrates this process by comparing the original token-level dependency graph with the merged word-level version. A detailed description of the merging procedure, along with transliteration and English glosses for the example sentence, is provided in Section 3.3.

This alignment is critical for ensuring consistent and interpretable graph structures. It eliminates discrepancies between the number of embedding vectors and graph nodes, enabling meaningful message passing and feature aggregation in the GNN. To our knowledge, this approach to harmonizing tokenization granularity in Arabic is novel and effectively addresses challenges posed by the language's rich morphology and syntactic structure.



(a) Original token-level dependency graph.



(b) Merged word-level dependency graph.

Figure 1: Comparison between token-level and merged word-level dependency graphs for the Arabic phrase كأنك مصاب بنزلة برد؟

3.3 Subword-to-Word Merging for Dependency Graphs

We parsed the Arabic sentence كأنك مصاب بنزلة برد؟ using CAMeLParser2.0, which outputs token-level dependencies, including affixes and clitics as separate units.

Sentence example with transliteration and translation:

Original: كأنك مصاب بنزلة برد؟
Transliteration: kÂnk mSAb bnzlh brd?
Translation: As if you have a cold?

Token list:

1. كأن — PRT (base)
2. +ك — PRON (enclitic)
3. مصاب — ADJ
4. +ب — ADP (prefix)
5. نزلة — NOUN
6. برد — NOUN
7. ؟ — PUNCT

Original edges (token-level): Token ID 0 refers to the artificial ROOT node.

- (1 → 0) —
- (2 → 1) SBJ
- (3 → 1) PRD
- (4 → 3) MOD
- (5 → 4) OBJ
- (6 → 5) IDF
- (7 → 1) MOD

Merging subword tokens: We merged:

- Tokens [1,2] → كأنك
- Tokens [4,5] → بنزلة

All incoming and outgoing edges of the merged tokens are also combined, so that the resulting word node preserves the original dependency relations for consistent graph construction.

Graph Construction We construct the input graph for the GNN as follows:

- **Nodes and node features**: Each node corresponds to a token w_i and is initialized with the corresponding BERT embedding $\mathbf{h}_i^{\text{BERT}}$. POS tags are encoded as learnable embeddings and concatenated to the token representations. The special `[CLS]` token is used to represent the syntactic root of the sentence and serves as the head node in the graph.
- **Edges and edge features**: Directed edges are constructed based on the dependency parse. Each edge is labeled with a dependency relation, which is encoded as a learnable embedding $\mathbf{e}_{\text{rel}}$ and incorporated via edge-aware message passing.

3.4 GNN Architecture and Training

We employ a multi-layer Graph Neural Network based on `TransformerConv` (Shi et al., 2021) layers to propagate syntactic information. Each TransformerConv layer uses multi-head self-attention (4 heads) over nodes, with attention scores modulated by edge attributes.

At layer l, the hidden state of node i is updated by attending over its neighbors $\mathcal{N}(i)$, conditioning on both node features and edge embeddings. Aggregated edge embeddings for incoming and outgoing edges are computed separately and fused into node representations through a linear projection. Formally, the node representations evolve as:

$$\mathbf{h}_i^{(l+1)} = \texttt{TransformerConv}\big(\mathbf{h}_i^{(l)}, \{\mathbf{h}_j^{(l)} : j \in \mathcal{N}(i)\}, \mathbf{e}_{rel}\big)$$

where $\mathbf{e}_{rel}$ are learned edge embeddings processed by an MLP.

After stacking TransformerConv layers with dropout and layer normalization, node features are aggregated via attentional pooling to produce a graph-level embedding $\mathbf{h}_S$.

This embedding is then fed into two parallel fully connected layers, generating logits for two complementary objectives:

$$\mathbf{z}_{\text{CORAL}} = \mathbf{W}_{\text{c}}\mathbf{h}_S + \mathbf{b}_{\text{c}}, \quad \mathbf{z}_{\text{QWK}} = \mathbf{W}_{\text{q}}\mathbf{h}_S + \mathbf{b}_{\text{q}}.$$

The first layer outputs 18 logits corresponding to ordinal thresholds for the CORAL loss (Cao et al., 2020), while the second produces 19 logits for direct classification used by the Quadratic Weighted Kappa (QWK) loss (de La Torre et al., 2018).

To balance ordinal accuracy and agreement quality, we optimize a combined loss:

$$\mathcal{L} = 0.5 \cdot \mathcal{L}_{\text{CORAL}} + 0.5 \cdot \mathcal{L}_{\text{QWK}},$$

where $\mathcal{L}_{\text{QWK}}$ penalizes larger prediction errors more heavily, enhancing robustness to class imbalance and ordinal inconsistencies.

Figure 2 illustrates the overall model pipeline, highlighting the integration of AraBERTv2 and syntactic parsing through a GNN layer for joint representation learning.

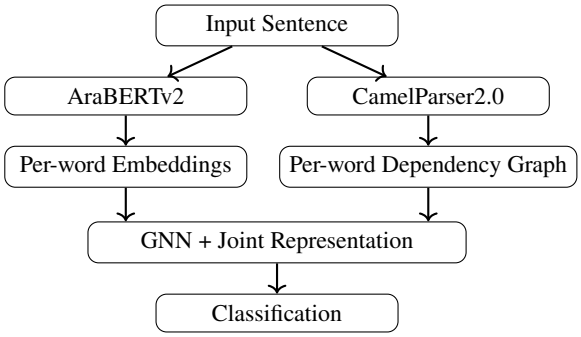


Figure 2: Model architecture integrating lexical and syntactic information for readability prediction.

4 Experimental Setup

4.1 Modeling and Preprocessing

We preprocess each sentence using WordPiece tokenization from AraBERTv2 and dependency parsing via `CamelParser2.0`, which outputs POS tags, syntactic relations, and token-level dependency structures. Following the word-to-subtoken alignment procedure detailed in 3.2, we average subtoken embeddings to form word-level representations. Correspondingly, subtoken-based nodes in the dependency graph are merged into single word-level nodes. The special `[CLS]` token is used to represent the syntactic root of the graph and serves as the anchor node for the sentence-level structure.

Our model integrates these word-level embeddings and dependency graphs through a 4-layer `TransformerConv`-based Graph Neural Network (GNN) with a hidden size of 512. We incorporate learnable embeddings for POS tags and dependency relations. Training is performed with the Adam optimizer using a learning rate of 1×10^{-4}, batch size of 64, dropout rate of 0.2, and early stopping based on validation loss.

Test Set	Model	QWK	Accuracy	Acc ±1	Dist	Acc 7	Acc 5	Acc 3
Internal	Baseline	80.2	**55.9%**	70.0%	1.1	**65.1%**	**69.4%**	**75.2%**
	Our Model	**83.7**	50.5%	**71.9%**	**1.0**	63.1%	68.0%	74.2%
Official Blind	Baseline	81.5	**58.1%**	**72.0%**	**1.0**	**67.7%**	**71.4%**	**76.5%**
	Our Model	**84.3**	51.0%	**72.0 %**	**1.0**	64.4%	68.7%	75.4%

Table 2: Performance on internal and official blind test sets for sentence-level readability prediction.

4.2 Evaluation Metrics

We treat readability assessment as an ordinal classification task. Our primary metric is **Quadratic Weighted Kappa (QWK)**, which penalizes larger prediction errors quadratically. We also report Exact Match Accuracy (Acc19) on the 19-level scale, along with adjacent accuracy (±1), coarser-grained accuracies (Acc7, Acc5, Acc3), and average prediction distance measured by mean absolute error.

5 Results

5.1 Comparison of Model Variants

We evaluate two model variants to assess the contribution of syntactic and structural information:

- **AraBERTv2 baseline**: Fine-tuned on the BAREC-Corpus-v1.0 Word input using cross-entropy loss (Elmadani et al., 2025b).
- **AraBERTv2 + GNN (ours)**: Our proposed approach integrates syntactic dependency parsing using a TransformerConv-based Graph Neural Network over word-level BERT embeddings. Each word node is enriched with POS and syntactic edge features, and the special `[CLS]` token anchors the graph as the syntactic root.

5.2 Performance on Internal and Official Test Sets

Table 2 shows our model achieves superior Quadratic Weighted Kappa (QWK) scores on both internal (83.7 vs. 80.2) and official blind test sets (84.3 vs. 81.5) compared to the baseline, indicating stronger ordinal agreement.

Our method also yields lower average prediction distances (1.0 vs. 1.1 internally) and competitive adjacent accuracy (±1), suggesting more calibrated and consistent predictions. While the baseline slightly outperforms in strict exact match accuracy, our model's improvements in ordinal metrics underscore the benefits of integrating syntactic structure.

6 Conclusion and Future Work

In this work, we explored the integration of contextual semantic features from AraBERTv2 with syntactic structure captured via dependency parsing graphs for the task of Arabic sentence-level readability assessment. Our model incorporates a TransformerConv-based GNN over a dependency graph constructed at the word level, resolving alignment inconsistencies between WordPiece tokenization and morphological segmentation. We demonstrated that augmenting AraBERTv2 with structural information significantly improves performance over a strong BERT-only baseline. Our findings highlight the value of syntactic context in modeling Arabic linguistic complexity and offer a promising direction for fine-grained readability prediction in morphologically rich languages.

For future work, we plan to investigate the use of multilingual pretrained models to leverage cross-lingual knowledge and improve generalization across different Arabic dialects and related languages. Additionally, exploring alternative architectures beyond encoder-only models, such as encoder-decoder or graph transformers, may further enhance the integration of syntactic and semantic information for readability prediction.

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A Appendix

A.1 Reproducibility Details

A.1.1 Data Preprocessing

- Sentences are cleaned and tokenized using CAMeL Tools.
- We additionally remove *tatweel* characters (ـ) from the text, as many were found to be broken or incorrectly inserted in the middle of words, which can negatively affect tokenization and model performance. For example, the word مدرّسة might appear as مدرّسـة, which we normalize by removing the tatweel and any extra spaces to restore the correct word form.
- POS tag IDs and dependency relation IDs are mapped using predefined dictionaries (`pos2id`, `dep2id`), which we constructed from the train set to cover all observed tags and relations.
- The graph is stored using PyTorch Geometric's `Data` objects with fields: `x`, `edge_index`, `edge_attr`, `pos_tag_ids`, and custom fields like `sentence`.

A.1.2 Model Components

1. AraBERTv2 (Encoder)

- Pretrained weights loaded from `aubmindlab/bert-base-arabertv02`.
- WordPiece tokenization applied via HuggingFace tokenizer.
- Hidden size: 768.
- For each token, embeddings are obtained by mean-pooling over all subtokens aligned via `encoding.word_ids()`, using the mean of the last 4 hidden layers' outputs.
- The first 8 layers of AraBERTv2 are frozen during training, and only the last 4 layers are fine-tuned.

2. Graph Construction

- Sentences are tokenized using CAMeL Tools' (Obeid et al., 2020) morphological segmenter.
- Dependency parses are extracted via the CamelParser2.0.
- For each sentence:
  - Nodes represent surface-level word tokens (segmented, not subword).
  - Directed edges represent syntactic dependencies (head → dependent).
  - Each edge is labeled by the dependency relation (e.g., `SBJ`, `OBJ`).
  - Part-of-speech (POS) tags are extracted per token.
  - The token labeled as `ROOT` by the parser is treated as the syntactic head of the sentence and serves as the root of the dependency tree.

3. Graph Neural Network Architecture Details

- **Node input:** Concatenation of AraBERTv2 embedding and averaged POS tag embedding (32-dimensional).
- **Edge input:** Relation type embedding (hidden size / 2), passed through a feedforward projection.
- **Convolution:** 4-layer `TransformerConv` (with 4 heads), using edge features in attention.

- **Edge Aggregation:** Mean aggregation of outgoing and incoming edge features per node.
- **Normalization:** LayerNorm applied after each GNN layer.
- **Pooling:** `AttentionalAggregation` over graph-level node embeddings.
- **Classifier heads:** One linear layer with $C - 1$ units for CORAL ordinal regression, and a separate linear head with C units for optimizing the Quadratic Weighted Kappa (QWK) loss.

A.2 Ablation Studies and Design Choices

During model development, we conducted extensive ablation studies to identify the most effective architectural components for our task. We evaluated various graph convolutional layers from the `torch_geometric.nn` library, including `NNConv`, `GCNConv`, `GATv2Conv`, and `GraphConv`. Among these, the `TransformerConv` layer consistently achieved the best performance, likely due to its ability to incorporate edge features directly into the attention mechanism and its use of multi-head attention, which captures complex relational patterns between nodes more effectively.

In terms of loss functions, we experimented with a range of objectives, including regression losses, cross-entropy loss, CORN loss (Shi et al., 2023), and direct optimization of the quadratic weighted kappa (QWK) metric. Our final setup combines CORAL loss (Cao et al., 2020) with the weighted QWK loss (de La Torre et al., 2018), yielding improved convergence and performance. This hybrid objective leverages the ordinal-aware structure of CORAL while directly aligning training with the evaluation metric through QWK.

These empirical findings guided our final model design. We recommend using the `TransformerConv` layer in conjunction with a CORAL + QWK loss for tasks involving graph-based ordinal classification.