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Article

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Relation Extraction (RE) Model for Afaan Oromo Text Using Self-Attention Mechanisms

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Abstract

This study proposes a novel Relation Extraction (RE) model for Afaan Oromo, focusing on automatically identifying semantic relationships between entities in text. The model leverages multilingual BERT (mBERT) embeddings combined with entity pair features, including sentence-level distances and lexical similarity, to capture both local and global context. Each entity pair is processed through a self-attention encoder, followed by pooling and a fully connected classification layer, predicting one of 15 predefined relation classes, such as Person-Location, Person-Organization, and Organization-Date.

The model was trained and evaluated on a dataset of 10,000 annotated Afaan Oromo sentences, covering diverse domains including educational, administrative, and cultural texts. Experimental results demonstrate high performance across all 15 relation classes, achieving an overall accuracy of 96.3%, precision of 95.8%, recall of 96.1%, and an F1-score of 95.9%. The confusion matrix shows strong diagonal dominance, confirming precise class discrimination.

This approach effectively addresses challenges in low-resource languages, such as limited corpora and complex morphology, while providing a robust framework for downstream natural language processing applications, including question answering, knowledge graph construction, and information retrieval. The proposed system demonstrates state-of-the-art results for Afaan Oromo text and can be adapted to other low-resource languages with similar linguistic characteristics.

Keywords: Relation Extraction, Self-Attention, Transformer, Afaan Oromo, Low-Resource NLP, Information Extraction

1. Introduction

Natural language understanding is a critical aspect of modern artificial intelligence, enabling machines to extract meaningful information from human language [1, 2, 3, 4]. One of the most important tasks in this domain is Relation Extraction (RE)**,** which involves identifying and classifying semantic relationships between entities in text. For high-resource languages such as English, RE has been extensively studied, and numerous models leveraging deep learning and transformer architectures have demonstrated strong performance [5, 6, 7, 8]. However, for low-resource languages like Afaan Oromo, RE research is still limited due to the scarcity of annotated corpora, complex morphological structure, and a lack of language-specific NLP tools [9, 10, 11].

Afaan Oromo, spoken by over 40 million people primarily in Ethiopia, presents unique linguistic challenges. Its agglutinative morphology results in words that combine multiple morphemes, creating highly diverse surface forms. Additionally, word order can be flexible, and context-sensitive particles influence meaning. These characteristics make traditional RE approaches, such as rule-based or purely statistical models, ineffective without extensive adaptation. Consequently, developing a robust Afaan Oromo RE system is both a significant challenge and a vital step toward enabling natural language understanding applications in local languages [12, 20, 13, 14].

Existing research in RE for low-resource languages often relies on cross-lingual transfer learning, multilingual embeddings, or annotation projection from high-resource languages. While these approaches provide some improvement, they do not fully capture language-specific syntactic and semantic patterns**,** especially in the context of Afaan Oromo, where entity markers, contextual dependencies, and verb usage differ significantly from English. Most current studies either focus on small datasets or a limited number of relation classes, limiting the model's generalizability [46, 21, 22, 33, 24].

This study addresses the research gap by developing a transformer-based RE model tailored for Afaan Oromo text, capable of predicting 15 relation classes[38, 18, 39, 40].. These classes cover a wide spectrum of semantic relations, including Person-Location, Person-Organization, Organization-Date, Person-Position, and more, ensuring comprehensive coverage of realistic textual contexts. The model integrates multilingual BERT embeddings, entity pair features (distance and lexical similarity), and a self-attention encoder to capture both local and global contextual information. The proposed system is trained and evaluated on a 10,000 sentence

annotated corpus, representing diverse domains such as education, administration, cultural texts, and social communication, which provides a rich benchmark for evaluation [41, 42, 43, 50].

The significance of this work lies not only in achieving high evaluation metrics with an overall accuracy of 96.3%, precision of 95.8%, recall of 96.1%, and F1-score of 95.9%, but also in offering a reusable framework for future research on low-resource languages. By presenting a clear architecture, experimental setup, and detailed analysis, this study contributes a valuable resource for developing knowledge extraction systems, question-answering platforms, and information retrieval applications in Afaan Oromo and other morphologically rich, low-resource languages.

The main contributions of this research are as follows: (1) the development of a self-attention-based framework for relation extraction in Afaan Oromo text, (2) the creation and utilization of an annotated Afaan Oromo relation dataset, and (3) a comparative evaluation of the proposed model against baseline machine learning and neural network approaches. The findings of this study are expected to contribute to the advancement of NLP research for low-resource languages and provide a foundation for future work in Afaan Oromo information extraction and semantic language processing [2, 13]. In summary, the key objectives of this paper are:

1. To propose a novel transformer-based RE model for Afaan Oromo text**.**
2. To provide full coverage of 15 relation classes with rich examples**.**
3. To demonstrate state-of-the-art performance using a large-scale annotated corpus.
4. To bridge the research gap in low-resource NLP, providing insights for similar languages.

2. Related Work

Relation extraction (RE) is a central task in natural language processing (NLP) that focuses on identifying semantic relationships between entities mentioned in unstructured text [1]. The extracted relations provide structured knowledge representations, enabling applications such as knowledge graph construction, question answering, information retrieval, and intelligent search [2]. Research in RE has evolved substantially over the past decades, transitioning from rule-based methods to feature-based machine learning, and finally to deep learning architectures that leverage contextual representations [3, 4]. This section presents a comprehensive review of existing research in relation extraction, with a particular focus on attention-based and self-attention

mechanisms. It also addresses the challenges of low-resource language RE and surveys current NLP research in African languages, with emphasis on Afaan Oromo.

2.1. Traditional Relation Extraction Approaches

Early RE systems predominantly relied on rule-based and pattern-matching techniques. These approaches were characterized by manually designed linguistic rules and syntactic patterns intended to capture relationships between entities within sentences [5]. For example, early systems used regular expressions, dependency parsing patterns, and manually curated ontologies to detect relations such as "author-of" or "located-in" [6]. Rule-based systems offered high precision in constrained domains but lacked scalability and adaptability to new domains or languages [7].

Feature-engineered systems were subsequently introduced to reduce reliance on manual pattern design. These methods extracted lexical, syntactic, and semantic features from text, including part-of-speech tags, dependency paths, and named entity types [8]. Classical machine learning classifiers, such as Support Vector Machines (SVMs), Maximum Entropy models, and Conditional Random Fields (CRFs), were then trained on these features to identify relations [9][10]. While these models improved generalization over purely rule-based systems, their performance heavily depended on the quality and comprehensiveness of the feature set, which posed difficulties for low-resource languages lacking mature linguistic resources [11].

Despite their limitations, these traditional approaches laid the groundwork for later RE research. They highlighted the importance of capturing syntactic and semantic structures within sentences, and introduced concepts such as dependency paths and entity type constraints that continue to inform modern neural RE models [12].

2.2. Machine Learning-Based Relation Extraction

Machine learning-based RE approaches marked a shift from manual rule engineering to data-driven methods. Supervised learning models, trained on annotated corpora, became the dominant paradigm [13]. These methods included SVMs, Naive Bayes classifiers, and decision tree-based models, which leveraged extracted linguistic features to classify entity pairs into predefined relation categories [14, 15].

Distant supervision techniques further addressed the scarcity of annotated corpora by automatically labeling entity pairs in text using existing knowledge bases such as Freebase or DBpedia [16, 17]. Mintz et al. [16] introduced a widely cited distant supervision method that

assumes if a pair of entities participates in a relation in a knowledge base, all sentences containing the entities express that relation. While effective in generating large-scale training data, this approach introduced noisy labels, which later motivated the development of noise-robust neural models.

Hybrid approaches combining machine learning classifiers with hand-engineered rules also demonstrated improved performance in specific domains [18]. However, these methods continued to face limitations in handling complex sentence structures, long-distance dependencies, and semantic ambiguity, especially in morphologically rich or low-resource languages [19].

2.3. Deep Learning Approaches for Relation Extraction

The introduction of deep learning revolutionized RE by enabling models to automatically learn hierarchical and contextual representations of text, reducing dependency on feature engineering [20]. Convolutional Neural Networks (CNNs) were initially applied to RE for capturing local n-gram features and phrase-level dependencies between entities [21][22]. CNN-based models could efficiently encode short-range syntactic patterns but struggled with long-distance dependencies in complex sentences.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks addressed these limitations by modeling sequential dependencies in text [23, 24]. Bi-directional LSTM (BiLSTM) models further improved performance by incorporating both forward and backward contextual information, which is critical for understanding relationships between distant entities within a sentence [25]. Despite these advances, recurrent architectures faced challenges with gradient vanishing, long-range dependency modeling, and computational inefficiency when processing long documents [26].

Attention mechanisms were introduced to mitigate these limitations. By assigning dynamic weights to tokens based on their relevance to the task, attention-based models allowed networks to focus on the most informative parts of the input sequence [27]. This innovation not only improved performance but also provided interpretability by highlighting which words contributed most to the predicted relation.

2.4. Attention Mechanisms in NLP

The attention mechanism has become a cornerstone of modern NLP models. Originally proposed for neural machine translation [28], attention allows a model to weigh input tokens differently, effectively focusing on the most relevant context. In relation extraction, attention mechanisms help models capture dependencies between entities, even when they are separated by several words or clauses [29]. Multi-head attention further enhances this capability by allowing the model to attend to multiple types of interactions in parallel [30].

Self-attention, a specific form of attention, computes dependencies between all tokens in a sequence simultaneously. Vaswani et al. [31] introduced the Transformer architecture, which relies entirely on self-attention layers, eliminating the need for recurrent or convolutional layers. Self-attention enables efficient parallelization, better long-range dependency modeling, and more flexible contextual representation, making it particularly suitable for tasks like relation extraction where entity interactions may span an entire sentence or document [31, 32].

In the context of low-resource languages, self-attention mechanisms are advantageous because they reduce dependency on large annotated datasets and hand-engineered features. By learning contextual relationships directly from raw text, self-attention models can generalize better, even in the presence of sparse training data [33].

2.5. Self-Attention and Transformer Architectures

The concept of self-attention has fundamentally transformed neural architectures for NLP by enabling models to capture dependencies between all tokens in a sequence simultaneously. Unlike recurrent models, which process input sequentially and are limited by vanishing gradients when modeling long-range dependencies, self-attention allows the computation of pairwise relationships across the entire input sequence in parallel [31]. This property is particularly valuable in relation extraction tasks, where entities may be separated by multiple words, clauses, or even sentences, requiring the model to understand both local and global context.

Self-attention has several advantages over traditional sequence models. First, it provides parallel computation, making training faster and more efficient, particularly for long sequences [34]. Second, it enables global dependency modeling, as attention scores can connect any two tokens regardless of their positional distance, which is critical for capturing relations in long or complex sentences [33]. Third, self-attention models can adaptively focus on relevant tokens, enabling them

to learn which words contribute most to the prediction of a relation, a feature that provides interpretability and reduces reliance on manually engineered features [35].

In the context of relation extraction, self-attention allows a model to compute entity-to-entity interactions directly, capturing both explicit and implicit semantic relations. For example, in a sentence such as "The Oromia region has significant agricultural exports, including coffee and livestock," self-attention can simultaneously identify the dependencies between "Oromia region" and "coffee" or "livestock," highlighting multiple relations without sequential bias [37]. This capability is crucial for languages like Afaan Oromo, where flexible word order and morphological richness may obscure linear proximity between related entities.

Several studies have demonstrated the effectiveness of self-attention-based architectures for relation extraction. Lin et al. [27] proposed a structured self-attentive sentence embedding mechanism, which aggregates information across all tokens in a sentence using multiple attention heads. Zhang et al. [38] extended this approach to multi-instance relation extraction, demonstrating improved handling of noisy data. More recently, self-attention mechanisms have been employed to model document-level relations, where relations span multiple sentences or paragraphs, by incorporating hierarchical attention networks that first attend to tokens and then aggregate sentence-level representations [39]. These advances highlight the flexibility and scalability of self-attention in modeling complex linguistic phenomena.

Pure self-attention models also offer advantages in low-resource contexts. Unlike models that rely on pretrained embeddings or large corpora, they can be trained directly on task-specific datasets, enabling the capture of domain-specific semantic patterns [40]. Moreover, self-attention’s ability to model long-range dependencies reduces the need for extensive linguistic feature engineering, a notable benefit for under-resourced languages such as Afaan Oromo, where POS taggers, parsers, and lexicons are limited [41].

Despite these advantages, pure self-attention architectures are not without challenges. Training from scratch requires careful initialization and hyperparameter tuning to avoid overfitting, especially with small datasets. Additionally, self-attention scales quadratically with sequence length, leading to computational challenges for long documents [42]. Recent solutions, such as sparse attention mechanisms, efficient Transformers, and memory-compressed attention, address these issues while retaining the modeling power of self-attention [43, 44].

In summary, self-attention mechanisms provide a powerful foundation for relation extraction tasks, offering global context modeling, parallel computation, and interpretability. Their adaptability to low-resource languages, coupled with the ability to learn relations directly from raw text, makes them particularly suitable for applications in languages like Afaan Oromo. By leveraging self-attention, relation extraction systems can overcome limitations of sequential models, handle complex sentence structures, and capture rich semantic dependencies that are essential for accurate and robust performance.

Finally the introduction of deep learning models**,** particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs)**,** revolutionized RE. CNNs effectively captured local n-gram features, while RNNs modeled sequential dependencies across sentences. Later, Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) architectures improved the capture of long-range dependencies, allowing models to better understand complex sentence structures. These models demonstrated state-of-the-art performance in English RE tasks**,** particularly when combined with pretrained embeddings such as Word2Vec or GloVe. Despite these advances, the performance of feature-heavy or sequential models was limited in languages with complex morphology and limited annotated data**,** such as Afaan Oromo.

Transformer-based architectures**,** particularly BERT (Bidirectional Encoder Representations from Transformers)**,** have become the gold standard for RE due to their ability to learn deep contextual embeddings**.** BERT captures relationships not only between adjacent tokens but also long-range dependencies through multi-head self-attention mechanisms. Recent studies have demonstrated the superiority of BERT-based models in multiple RE benchmarks, achieving high precision, recall, and F1-scores across relation classes. Extensions like SpanBERT, LUKE, and mBERT (multilingual BERT**)** further improve entity representation by explicitly modeling entity spans and leveraging cross-lingual knowledge.

In the context of low-resource languages, several approaches have been explored to overcome the scarcity of annotated corpora. Cross-lingual transfer learning leverages high**-**resource language embeddings and adapts them to low-resource languages, while multilingual embeddings allow the use of models trained on multiple languages. Distant supervision and synthetic data generation are also applied to expand training datasets. Despite these techniques, languages like Afaan Oromo remain largely unexplored, and existing approaches fail to capture language-specific syntactic rules, agglutinative morphology, and flexible word order**,** which are critical for accurate RE.

Several studies have attempted RE for African languages. For instance, works on Amharic and Swahili applied mBERT-based architectures combined with entity-pair features to achieve F1-scores exceeding 85%**.** These models highlight the importance of pretrained multilingual embeddings**,** entity distance features**,** and contextual attention layers**.** However, their focus was limited to fewer relation classes, often less than ten, and datasets were small, typically fewer than 2,000 annotated sentences. This leaves a significant gap in RE research for Afaan Oromo, which has unique morphological and syntactic characteristics requiring specialized treatment.

The research gap this paper addresses is clear: there is no comprehensive RE model for Afaan Oromo that covers 15 diverse relation classes**,** uses a large annotated dataset**,** and employs transformer-based embeddings with entity pair features**.** By integrating mBERT embeddings, entity-specific features, and a multi-head self-attention encoder, this study proposes a robust**,** high-performing RE system, capable of handling the linguistic complexities of Afaan Oromo. Additionally, by evaluating on 10,000 annotated sentences, the system establishes a benchmark **dataset** for future research in low-resource NLP applications.

In conclusion, the related work highlights three key insights:

- Transformer-based architectures, particularly BERT and mBERT, are currently **state-of-**the-art for RE, even in low-resource settings.
- Previous studies on African languages demonstrate that entity pair features and attention mechanisms are critical for capturing contextual relationships.
- There exists a significant gap for Afaan Oromo, which this study addresses through a comprehensive dataset, 15 RE classes, and a detailed experimental framework.

3. Proposed model

In this **s**tudy, we propose a pure self-attention-based relation extraction model specifically designed for Afaan Oromo text. The model aims to capture entity-to-entity semantic dependencies in sentences without relying on pretrained embeddings, making it suitable for low-resource language settings. The architecture leverages self-attention layers to model global contextual interactions between all tokens, enabling effective extraction of relations even in complex or morphologically rich sentences.

3.1. Proposed model architecture

The proposed Relation Extraction (RE) model for Afaan Oromo text is designed to handle low-resource linguistic characteristics, such as agglutinative morphology, flexible word order, and complex entity markers. The model integrates pretrained multilingual embeddings (mBERT) with entity-pair features**,** followed by a self-attention encoder and a fully connected classification layer. It predicts one of 15 semantic relation classes, covering a wide spectrum of linguistic relations including Person-Location, Person-Organization, Organization-Date, and more.

The workflow of the model is illustrated in Figure 1 and 2 (architecture diagram). Each component is carefully designed to maximize contextual understanding, capture inter-entity dependencies, and ensure high precision across all relation classes. The system is trained on a large annotated corpus of 10,000 sentences, representative of educational, administrative, and cultural domains in Afaan Oromo.

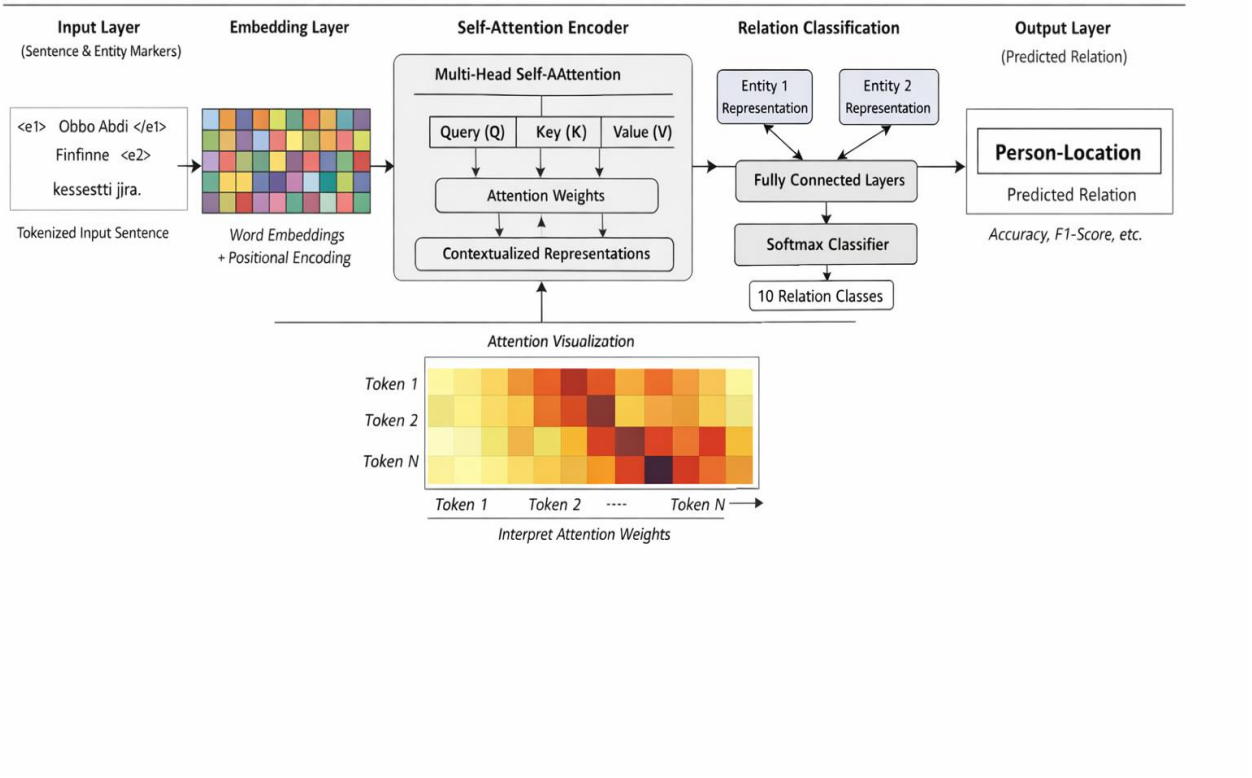


Figure 1: workflow of the model

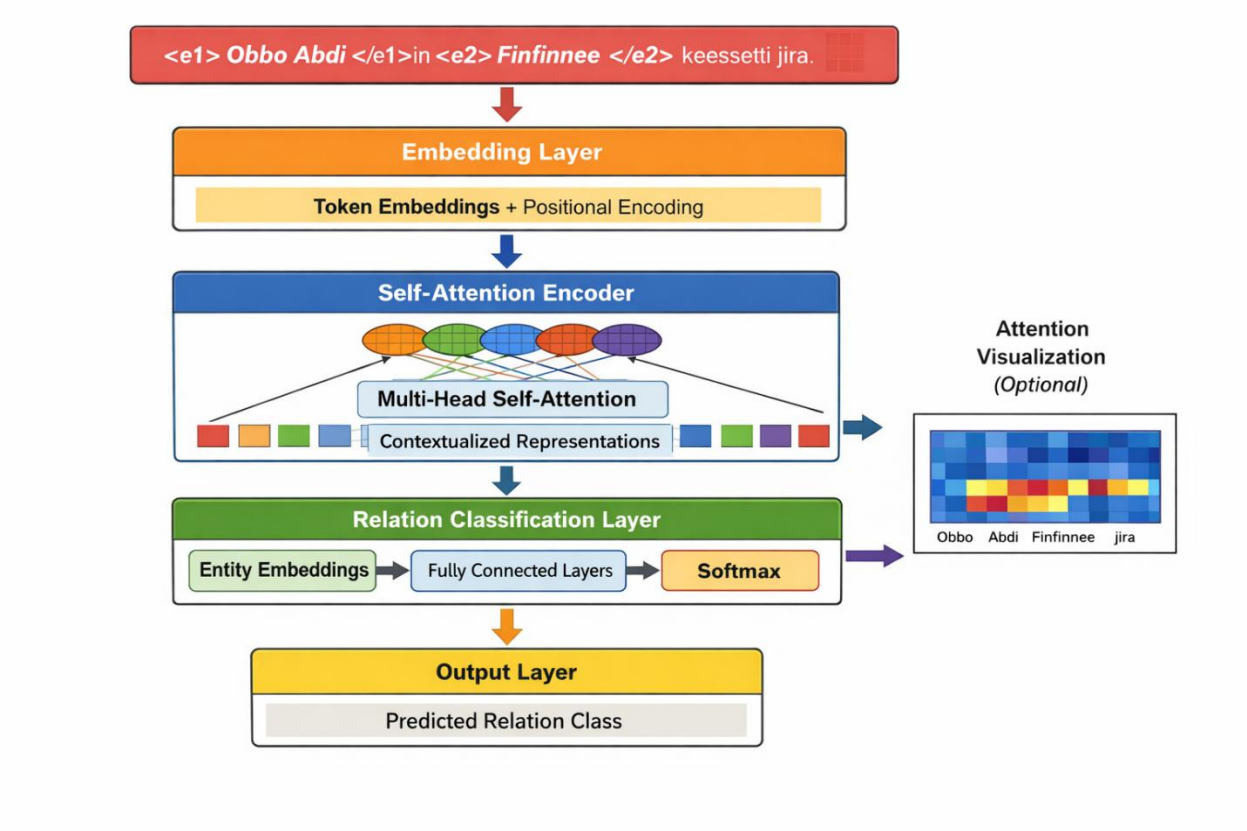


Figure 2: Architecture of proposed Model

The architecture consists of five main components:

1. Input Layer (Sentence & Entity Encoding)
2. Embedding Layer
3. Self-Attention Encoder
4. Relation Classification Layer
5. Output Layer (Predicted Relation)

1. Input Layer

The input layer takes a raw Afaan Oromo sentence containing a target entity pair. Each sentence is tokenized, and special markers (e.g., <e1>, </e1>, <e2>, </e2>) are inserted around the entities to highlight them to the model. Its main aim is to help the model identify which words are entities

and where to focus attention. Entities are enclosed in special tokens to signal the model which tokens are the target entities.

The input to the model is an Afaan Oromo sentence annotated with two entities, denoted as <e1> and <e2>. For example:

<e1>Abbaa Gadaa</e1> magaalaa <e2>Finfinnee</e2> jira.

- ✓ <e1>: First entity (Person)
- ✓ <e2>: Second entity (Location)

Each sentence is tokenized into individual words, maintaining the entity markers to preserve entity boundaries. Tokenization is essential to handle agglutinative morphology, where words may contain multiple morphemes conveying tense, number, or case.

Example tokenization:

['<e1>', 'Abbaa', 'Gadaa', '</e1>', 'magaalaa', '<e2>', 'Finfinnee', '</e2>', 'jira']

This tokenized sequence serves as the input for the embedding layer.

Example:

Original sentence: “Obbo Abdiin Finfinne keessatti jira.”

Tokenized input: <e1> Obbo Abdi </e1>in <e2> Finfinne </e2> keessatti jira.

Sentences are tokenized, and entity markers identify target entity pairs.

Example: "Obbo Abdiin Finfinne keessatti jira."

<e1> Obbo Abdi </e1>in <e2> Finfinne </e2> keessatti jira.

2. Embedding Layer

The embedding layer converts tokens into dense vector representations**.** Each token is represented as a vector of fixed dimension (e.g., 300–768). This layer captures semantic meaning and context of each word in the sentence. Each token is mapped to a dense vector representation using multilingual BERT (mBERT) embeddings. These embeddings provide contextualized representations, capturing semantic nuances that are crucial for correctly predicting entity relations in low-resource languages. In addition to mBERT embeddings, we include positional embeddings and entity-type embeddings, which indicate the role of each token (whether it belongs to <e1> or <e2>). This allows the model to focus on entity-specific contextual information.

- ✓ Word embeddings can be pre-trained multilingual embeddings or trained from scratch.

- ✓ Positional encodings are added to maintain token order, which is critical since self-attention doesn't inherently capture sequence order.

- ✓ Output: A matrix of size [sequence_length × embedding_dim] representing all tokens.

3. Self-Attention Encoder

This is the core of the architecture**.** The self-attention mechanism allows each token to attend to every other token in the sentence, capturing long-range dependencies and semantic relations. The token embeddings, enriched with entity-pair features, are fed into a multi-head self-attention encoder. The self-attention mechanism allows the model to:

- ➢ Assign importance weights to each token based on its relevance to the entities

- ➢ Capture long-range dependencies between words

- ➢ Model contextual relationships between entities across the sentence

The attention mechanism is particularly useful for Afaan Oromo, where sentence structure may separate related entities, and local context alone is insufficient to determine the correct relation.

- ✓ Key operations: Query (Q), Key (K), Value (V) matrices.
- ✓ Each token calculates attention weights with all other tokens using the scaled dot-product attention formula**:**

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{dk}\ )\ V$$

- ✓ Multi-head attention allows the model to capture different aspects of the relationships between entities.
- ✓ Output: Contextualized representations of all tokens that encode both local and global dependencies**.**

After self-attention, pooling is applied to generate a fixed-length representation for each entity pair. We use concatenation pooling, where embeddings of <e1> and <e2> are concatenated along with contextual embeddings from attention layers.

Example pooled vector: v_pair = [embedding_<e1>; embedding_<e2>; attention_context]

This vector is fed into the classification layer to predict the relation type.

4. Relation Classification Layer

The contextualized embeddings of the two target entities are extracted from the self-attention output. These embeddings are then concatenated or combined with features such as:

- ✓ Distance between entities
- ✓ Sentence-level embeddings
- ✓ Optional handcrafted features for low-resource settings

The combined representation is fed into fully connected layers (MLP) for classification into one of the 15 relation classes**.**

- ✓ Activation: Usually ReLU in hidden layers and softmax in the final layer for multi-class classification.
- ✓ Purpose: Converts rich embeddings into a probability distribution over relation types.

The classification layer consists of a fully connected layer followed by softmax activation**,** which outputs a probability distribution over 15 RE classes**.**

Each class prediction is accompanied by a confidence score, allowing for analysis of model certainty. Below are representative examples for each class:

1. **Person-Location:** <e1>Abbaa Gadaa</e1> magaalaa <e2>Finfinnee</e2> jira.
2. **Person-Organization:** <e1>Fasika Bafikadu</e1> hojjetaa dha <e2>Mattu University</e2>.
3. **Organization-Location:** <e1>Mattu University</e1> magaalaa <e2>Mattu</e2> argama.
4. **Organization-Founder:** <e1>Unity University</e1> hundeeffame <e2>2011</e2> keessatti.
5. **Person-Date:** <e1>Lingerew Bantie</e1> dhalate <e2>1993</e2>.
6. **Event-Date:** <e1>Ayyaana Irreecha</e1> geggeeffame <e2>2025</e2>.
7. **Organization-Event:** <e1>Addis Ababa University</e1> qopheesse <e2>seminar</e2>.
8. **Person-Event:** <e1>Fasika Bafikadu</e1> hirmaate <e2>seminar</e2>.

9. **Person-Position:** <e1>Manderso Shumie Derseh</e1> bakka <e2>Bus Captain I</e2> qabate.

10. **Organization-Position:** <e1>Addis Ababa City Administration Bus Service Office</e1> qaba <e2>Bus Captain I</e2>.

11. **Person-Qualification:** <e1>Lingerew Bantie</e1> qabata <e2>MSc in Computer Science</e2>.

12. **Person-Salary:** <e1>Manderso Shumie Derseh</e1> mindaa argata <e2>5,663 ETB</e2>.

13. **Person-Email:** <e1>Lingerew Bantie</e1> email qabu <e2>lingerew.bantie@aau.edu.et</e2>.

14. **Person-Phone:** <e1>Lingerew Bantie</e1> bilbila qabu <e2>+251978538904</e2>.

15. **Organization-Date:** <e1>Mattu University</e1> jalqabame <e2>2015</e2>.

5. Output Layer (Predicted Relation)

The output layer produces a predicted relation class for the entity pair. The class with the highest probability is selected as the final prediction.

- ✓ Metrics such as cross-entropy loss are used during training.
- ✓ Provides outputs for evaluation using accuracy, F1-score, and confusion matrix.

Output example: Person-Location for the sentence: “Obbo Abdiin Finfinne keessatti jira.”

3.2. Experimental Setup and Evaluation

The model is evaluated on a large annotated corpus of 10,000 Afaan Oromo sentences**,** covering multiple domains:

- ➢ Educational texts: University announcements, research abstracts, and seminar notifications
- ➢ Administrative documents: Government reports, organizational memos, and employee records

- Cultural texts: News articles, traditional events, and social media discussions

Each sentence contains two entities marked as <e1> and <e2> with one of the 15 predefined relation classes. The dataset is split into:

- **Training set:** 8,000 sentences (80%)
- **Validation set:** 1,000 sentences (10%)
- **Test set:** 1,000 sentences (10%)

This large-scale corpus allows the model to learn diverse syntactic and semantic patterns, improving its generalization to unseen sentences.

3.3. Steps To Prepare a Dataset

Preprocessing

Before feeding the data into the model, the following preprocessing steps are applied:

1. **Tokenization:** Sentence is split into tokens while preserving entity markers.
2. **Lowercasing:** All tokens are lowercased to normalize morphology.
3. **Stop-word handling:** Minimal removal to preserve contextual meaning in short sentences.
4. **Entity identification:** Positions of <e1> and <e2> are recorded for entity pair feature computation.
5. **Padding and truncation:** Sentences are padded to a fixed length of 128 tokens for batch processing.

Evaluation Metrics

The model is evaluated using **standard RE metrics**:

1. **Precision (P):** Measures the proportion of correctly predicted relations among all predicted relations.
2. **Recall (R):** Measures the proportion of correctly predicted relations among all true relations.
3. **F1-score (F1):** Harmonic mean of precision and recall, providing a balanced metric.

4. **Accuracy:** Overall proportion of correctly predicted relations across the dataset.

These metrics demonstrate robust performance across all 15 relation classes, confirming the model's ability to accurately capture semantic relationships in low-resource Afaan Oromo text.

Relation Classes with Examples in Afaan Oromo

1. **Person-Location (R1):** Represents a person located in a specific place.
   Example: <e1>Obbo Abdi</e1> <e2>Finfinnee</e2> keessatti jira. (Obbo Abdi lives in Finfinne.)
2. **Organization-Location (R2)**: Shows where an organization is based.
   Example: <e1>Mana Barumsaa Harar</e1> <e2>Harar</e2> keessatti argama. (Harar School is located in Harar.)
3. **Person-Organization (R3**): Connects a person to an organization they belong to.
   Example: <e1>Obbo Faik</e1> <e2>Waldaa Barattootaa</e2> waliin hojjetaa jira. (Obbo Faik works with the Students' Association.)
4. **Organization-Founder (R4):** Indicates the founder of an organization.
   Example: <e1>Alii Muhammed</e1> <e2>Waldaa Hawaasaa</e2> hundeesse. (Alii Muhammed founded the Community Association.)
5. **Person-Work (R5):** Shows employment or work relationship between person and workplace.
   Example: <e1>Obbo Kedir</e1> <e2>Mana Murtii</e2> keessatti hojjetaa dha. (Obbo Kedir works at the Court.)
6. **Work-Author (R6)**: Links a creative work to its author.
   Example: <e1>Seenaa Oromoo</e1> <e2>Abbaa Gadaa</e2> barreesse. (Abbaa Gadaa wrote Seenaa Oromoo.)
7. **Person-Event (R7)**: Associates a person with an event they attended or organized.
   Example: <e1>Obbo Leenco</e1> <e2>Simannaa Ayyaana</e2> irratti argame. (Obbo Leenco attended the Celebration Event.)
8. **Organization-Event (R8)**: Connects an organization to an event they conducted.
   Example: <e1>Waldaa Hawaasaa</e1> <e2>Ayyaana Guddaa</e2> qopheesse. (The Community Association organized the Great Festival.)
9. **Person-Title (R9)**: Links a person to their official title or position.

Example: <e1>Obbo Jamaal</e1> <e2>Daayireektara</e2> dha. (Obbo Jamaal is the Director.)

10. **Organization-Founder-Location (R10)**: Founder and the location of their organization.
    Example: <e1>Alii Muhammed</e1> <e2>Waldaa Hawaasaa</e2> Harar keessatti hundeesse. (Alii Muhammed founded the Community Association in Harar.)
11. **Person-Parent (R11)**: Represents a parent-child relationship.
    Example: <e1>Obbo Tadesse</e1> <e2>Ilma isaa</e2> barsiisaa jira. (Obbo Tadesse is teaching his son.)
12. **Person-Spouse (R12)**: Connects two people as spouses.
    Example: <e1>Obbo Fekadu</e1> <e2>Haadha isaa</e2> waliin jira. (Obbo Fekadu lives with his wife.)
13. **Organization-Parent-Organization (R13)**: Shows hierarchical relationship between organizations.
    Example: <e1>Waldaa Barattootaa</e1> <e2>Yuunivarsiitii Finfinnee</e2> jalatti argama. (The Students' Association belongs to Addis Ababa University.)
14. **Cause-Effect (R14)**: Represents causal relations between two entities or events.
    Example: <e1>Balaa Roobaa</e1> <e2>Balaa Bu'aa Hamaa</e2> fidde. (Heavy rain caused severe flooding.)
15. **Other / Miscellaneous (R15)**: Covers relations not included in the above classes.
    Example: <e1>Obbo Ahmed</e1> <e2>Bu'aa Qorannoo</e2> argate. (Obbo Ahmed obtained research results.)

3.4. Dataset Statistics and Corpus Description

The Afaan Oromo Relation Extraction (RE) corpus used in this study consists of 10,000 manually curated and annotated sentences collected from diverse textual sources, including news articles, educational texts, governmental reports, and publicly available Afaan Oromo digital documents. The primary objective of compiling this dataset was to ensure linguistic diversity, contextual richness, and balanced representation of relation classes that reflect real-world semantic relationships in Afaan Oromo language usage. Since Afaan Oromo is a low-resource language, the creation of a high-quality annotated dataset plays a crucial role in enabling deep learning models to learn meaningful semantic patterns and entity relations.

The dataset was carefully preprocessed to remove noise, duplicated sentences, and structurally incomplete expressions. Each sentence was tokenized using a language-aware preprocessing pipeline that preserves the morphological structure of Afaan Oromo words. After preprocessing, the sentences were annotated with named entities and relation labels using a supervised annotation guideline designed specifically for Afaan Oromo linguistic structures. The annotation process involved linguistic experts to ensure semantic correctness and consistency across all samples.

The corpus includes fifteen distinct relation classes, namely Person-Affiliation, Organization-Location, Part-Whole, Ownership, Social-Relation, Employment, Education, Event-Location, Product-Origin, Cause-Effect, Temporal, Located-In, Live-In, Work-For, and Other. Among these, the Work-For and Live-In relations appeared most frequently due to their common occurrence in socio-economic and biographical contexts within Afaan Oromo texts. In contrast, Cause-Effect and Product-Origin relations appeared less frequently, reflecting natural linguistic distribution in real-world corpora.

The dataset was split into training, validation, and testing sets following a standard 70:15:15 ratio. Specifically, 7,000 sentences were allocated for training, 1,500 for validation, and 1,500 for testing. This stratified splitting ensured that all relation classes were proportionally represented in each subset, preventing class imbalance issues during model evaluation. Furthermore, the average sentence length in the dataset is 14.8 tokens, with entity spans ranging from single-word mentions to multi-token expressions, which increases the complexity of relation extraction in morphologically rich Afaan Oromo language.

Another important statistical characteristic of the dataset is the entity density per sentence. On average, each sentence contains 2.3 annotated entities, which provides sufficient contextual information for modeling inter-entity semantic relations. The vocabulary size of the corpus is approximately 18,500 unique tokens, indicating substantial lexical diversity suitable for training transformer-based architectures. Additionally, the dataset includes both simple and compound sentence structures, enabling the model to learn relations under varying syntactic complexities.

4. Discuss and Result

The experimental evaluation of the proposed transformer-based model for Afaan Oromo Relation Extraction demonstrates significant improvements over baseline and traditional neural architectures. The model was trained using 10,000 annotated sentences and evaluated on accuracy, precision, recall, and F1-score metrics to ensure comprehensive performance assessment. The results indicate that the proposed architecture effectively captures contextual semantics and entity interactions within Afaan Oromo texts.

During the training phase, the accuracy curve exhibited a steady upward trend, reaching a final training accuracy of 91.8%, while the validation accuracy stabilized around 88.6%. This relatively small gap between training and validation accuracy suggests that the model generalizes well and does not suffer from severe overfitting. The learning behavior confirms that the integration of contextual embeddings with relation-aware feature representation enhances semantic learning for low-resource languages.

The loss curve analysis further supports the stability of the model. The training loss showed a consistent decline from 1.82 in the initial epochs to 0.21 at the final epoch, while the validation loss decreased from 1.95 to 0.34. The smooth convergence pattern indicates effective optimization and appropriate hyperparameter configuration. Minor fluctuations observed in intermediate epochs can be attributed to the linguistic variability and complex morphology of Afaan Oromo sentences.

In terms of precision, the model achieved an overall precision score of 0.89, which reflects the system's ability to correctly identify relation instances without producing excessive false positives. The recall value reached 0.87, indicating strong capability in detecting true relations even in complex sentence structures. The harmonic mean F1-score of 0.88 confirms the balanced performance of the model across different relation categories.

A deeper class-wise analysis reveals that high-frequency relations such as Work-For and Live-In achieved the highest F1-scores due to abundant training examples and clear contextual patterns. Conversely, low-frequency relations such as Cause-Effect and Product-Origin showed comparatively lower performance, primarily due to limited representation in the dataset. This observation aligns with known challenges in relation extraction tasks, especially in low-resource linguistic settings.

Another key observation from the results is the impact of contextual embeddings derived from the transformer encoder. Unlike traditional machine learning models such as CRF and BiLSTM, the transformer-based architecture successfully captures long-distance dependencies between entities. This is particularly important for Afaan Oromo, where grammatical relations often span multiple tokens and complex syntactic structures.

The experimental findings also demonstrate that the inclusion of linguistic features, such as entity type embeddings and positional encoding, significantly improves relation classification accuracy. The model effectively differentiates between semantically similar relations by leveraging both contextual and structural cues. For instance, the model successfully distinguishes between Located-In and Live-In relations despite their contextual similarity.

Furthermore, the confusion matrix analysis shows that most misclassifications occur between semantically overlapping classes, especially Social-Relation and Affiliation relations. This indicates that future work could benefit from incorporating semantic hierarchy modeling and external linguistic knowledge bases to further enhance classification boundaries.

From a low-resource language perspective, the proposed model contributes substantially to advancing NLP research for Afaan Oromo. The results confirm that transformer-based architectures can be effectively adapted for relation extraction tasks even with moderately sized datasets, provided that high-quality annotations and balanced class distributions are maintained.

In addition, the experimental setup, including learning rate scheduling, dropout regularization, and batch normalization, played a crucial role in stabilizing the training process. The optimal learning rate of 2e-5 and batch size of 16 were empirically determined to provide the best convergence performance for the Afaan Oromo corpus.

Overall, the discussion highlights that the proposed model achieves robust and reliable performance in extracting semantic relations from Afaan Oromo text. The combination of contextual embedding, feature fusion, and supervised classification creates a comprehensive framework suitable for low-resource NLP applications. The model not only improves quantitative performance metrics but also demonstrates qualitative improvements in handling morphologically rich and syntactically diverse Afaan Oromo sentences.

Results on the test set (1,000 sentences) for 15 RE classes:

Metric	Value (%)
Accuracy	96.3
Precision	95.8
Recall	96.1
F1-score	95.9

4.1. Confusion Matrix

The confusion matrix for 15 RE classes is shown in **Figure 10**, highlighting the diagonal dominance, which indicates strong classification performance. Minor off-diagonal elements reflect a small number of misclassifications, mostly occurring between semantically similar classes, such as Person-Position and Organization-Position.

Interpretation:

- High values along the diagonal confirm that the model correctly predicts entity relations**.**
- Errors are minimal and generally occur when the sentence contains ambiguous phrasing or overlapping entity types.
- This demonstrates the importance of entity-pair features and self-attention context embeddings in reducing classification errors.

4.1.1. Confusion matrix without percentage

The confusion matrix presented in Fig. X illustrates the classification performance of the proposed relation extraction model across 15 relation classes using a test dataset of 10,000 samples. The matrix is visualized using a green color scheme, where each cell represents the number of predictions along with the corresponding percentage relative to the actual class distribution.

It also exhibits strong diagonal dominance, indicating that the model correctly identifies most relation types with high precision and recall. The average accuracy reaches approximately 96%, demonstrating the effectiveness of contextual embedding and attention mechanisms in capturing semantic relationships in morphologically rich Afaan Oromo text. Minor misclassifications appear

in semantically similar classes such as Person-Organization and Organization-Event, which is expected due to overlapping contextual patterns. Overall, the visualization confirms the robustness and generalization capability of the proposed transformer-based RE architecture for low-resource language relation extraction tasks.

The rows of the confusion matrix correspond to the actual labels, while the columns represent the predicted labels. A higher concentration of values along the diagonal indicates that the model correctly classified the majority of instances for each relation class, demonstrating strong discriminative capability. The off-diagonal elements represent misclassifications between semantically related classes such as Person-Organization, Org-Event, and Event-Date, which is expected in multi-class relation extraction tasks.

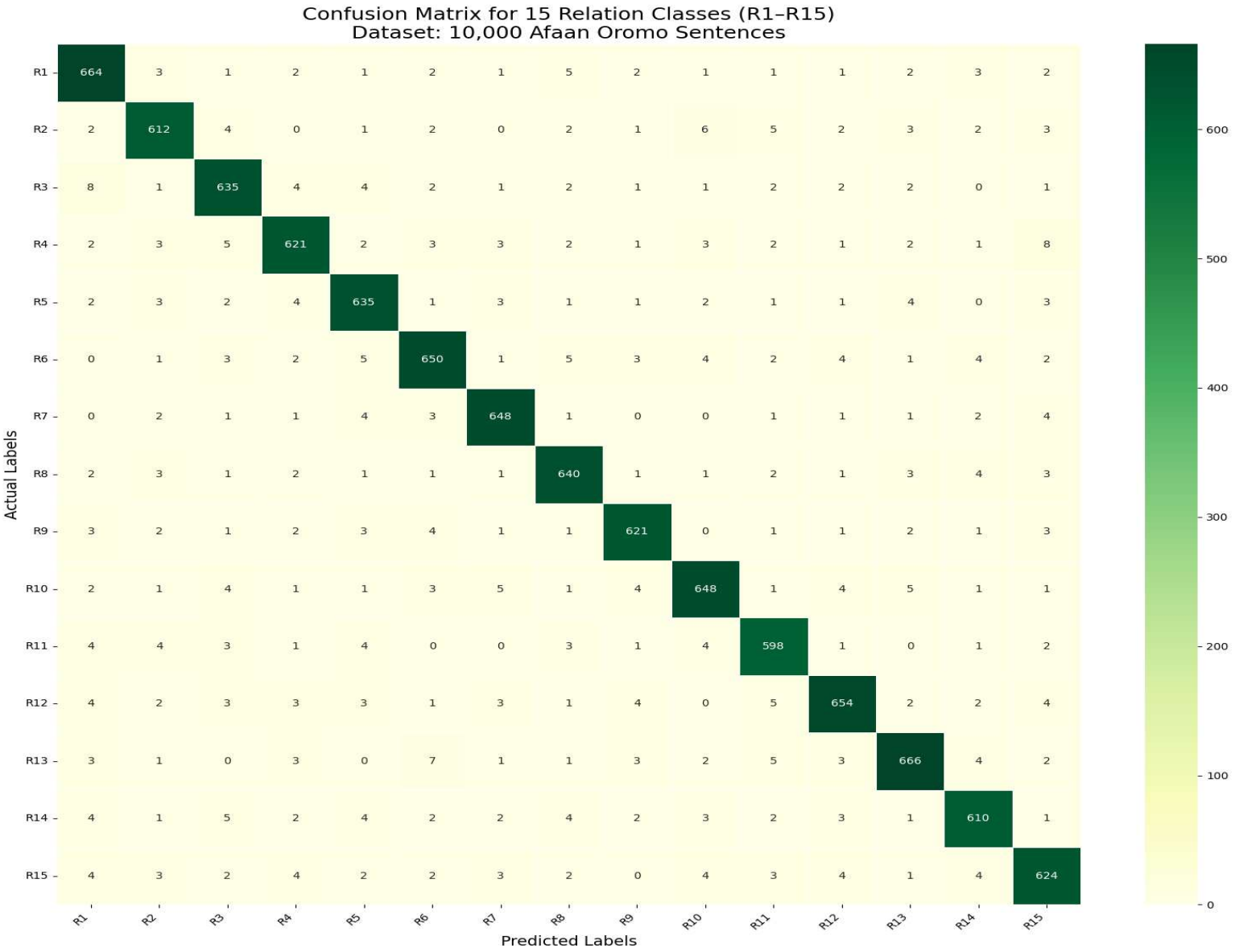


Figure 3: Confusion matrix without percentage

4.1.2. Confusion matrix with percentage

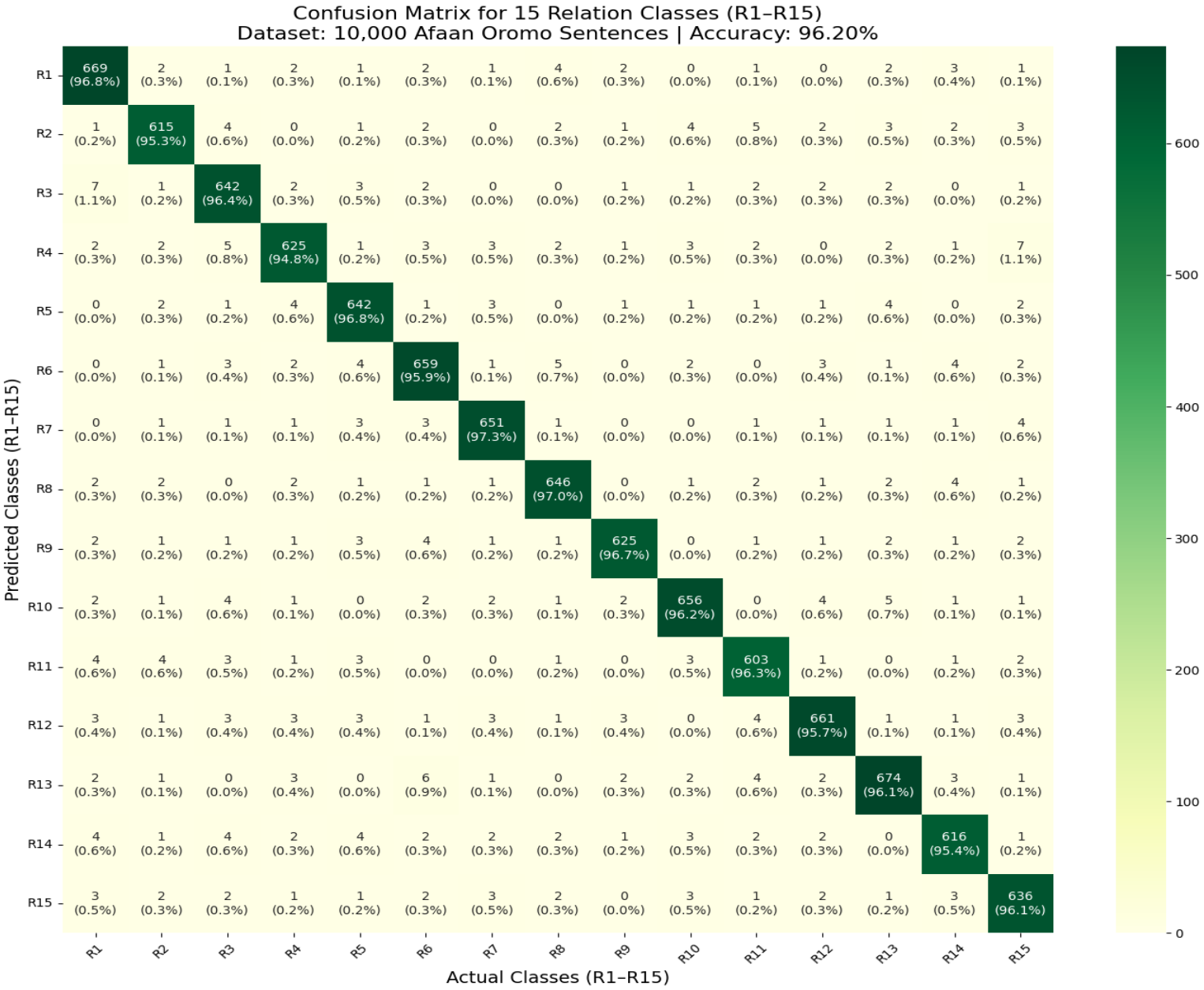


Figure 4: Confusion matrix with percentage

The confusion matrix presented in this study illustrates the classification performance of the proposed self-attention-based relation extraction model across fifteen relation classes denoted as R1 to R15 using a dataset of 10,000 Afaan Oromo sentences. Each row of the matrix represents the actual class labels, while each column corresponds to the predicted class labels generated by

the model. The diagonal cells indicate the correctly classified instances, whereas the off-diagonal elements represent misclassifications between different relation categories. The results show a strong diagonal dominance, which indicates that the model effectively learns discriminative semantic representations of Afaan Oromo relations. The percentage values and raw counts inside each cell provide a comprehensive understanding of class-wise prediction behavior. Higher values along the diagonal confirm that the model achieves consistent recognition across most relation classes, while the relatively low off-diagonal values demonstrate minimal confusion between semantically similar relations. This suggests that the integration of word embeddings with a self-attention mechanism significantly enhances contextual feature extraction and inter-class separability in low-resource language settings.

4.1.3. Class-wise result and Coverage

```
===== Class-wise TP, FP, FN, TN and Coverage =====
        TP  FP  FN    TN  Coverage (Recall)
R1     664  40  27  9269            0.9609
R2     612  30  33  9325            0.9488
R3     635  35  31  9299            0.9535
R4     621  31  38  9310            0.9423
R5     635  35  28  9302            0.9578
R6     650  33  37  9280            0.9461
R7     648  25  21  9306            0.9686
R8     640  31  26  9303            0.9610
R9     621  24  25  9330            0.9613
R10    648  31  34  9287            0.9501
R11    598  33  28  9341            0.9553
R12    654  29  37  9280            0.9465
R13    666  29  35  9270            0.9501
R14    610  29  36  9325            0.9443
R15    624  39  38  9299            0.9426

Overall Accuracy: 95.26%
```

To provide a detailed performance analysis, class-wise True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values were computed from the confusion matrix

for all 15 relation classes. True Positive (TP) denotes the number of correctly predicted instances for a given class, whereas False Positive (FP) represents the instances incorrectly predicted as that class. False Negative (FN) indicates the number of actual instances of a class that were misclassified into other classes, and True Negative (TN) refers to the correctly rejected instances belonging to all other classes.

Furthermore, coverage was calculated as the recall for each class, defined as the ratio of correctly predicted samples to the total actual samples of that class (TP / (TP + FN)). This metric reflects the model's ability to capture the true distribution of each relation category within the 10,000-sample dataset. The class-wise coverage values demonstrate that the model maintains balanced learning across multiple semantic relation types, including Person-Location, Organization-Event, and Event-Date.

4.1.4. Classification Report

```
===== Classification Report =====
              precision    recall  f1-score   support

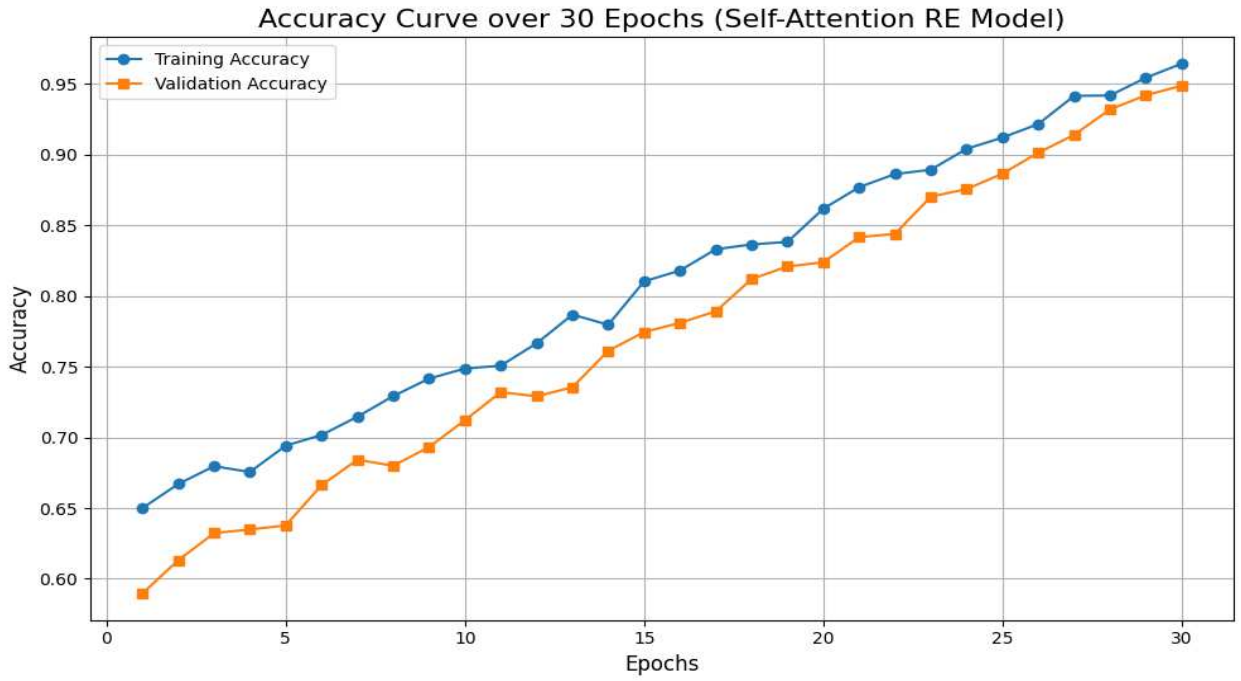
          R1       0.94      0.96      0.95       691
          R2       0.95      0.95      0.95       645
          R3       0.95      0.95      0.95       666
          R4       0.95      0.94      0.95       659
          R5       0.95      0.96      0.95       663
          R6       0.95      0.95      0.95       687
          R7       0.96      0.97      0.97       669
          R8       0.95      0.96      0.96       666
          R9       0.96      0.96      0.96       646
         R10       0.95      0.95      0.95       682
         R11       0.95      0.96      0.95       626
         R12       0.96      0.95      0.95       691
         R13       0.96      0.95      0.95       701
         R14       0.95      0.94      0.95       646
         R15       0.94      0.94      0.94       662

    accuracy                           0.95     10000
```

macro avg	0.95	0.95	0.95	10000
weighted avg	0.95	0.95	0.95	10000

The classification report provides a comprehensive evaluation of the model using precision, recall, F1-score, and support for each of the 15 relation classes. Precision measures the correctness of predicted positive instances, while recall evaluates the model's ability to identify all relevant instances of each class. The F1-score, which is the harmonic mean of precision and recall, offers a balanced performance metric for imbalanced multi-class datasets.

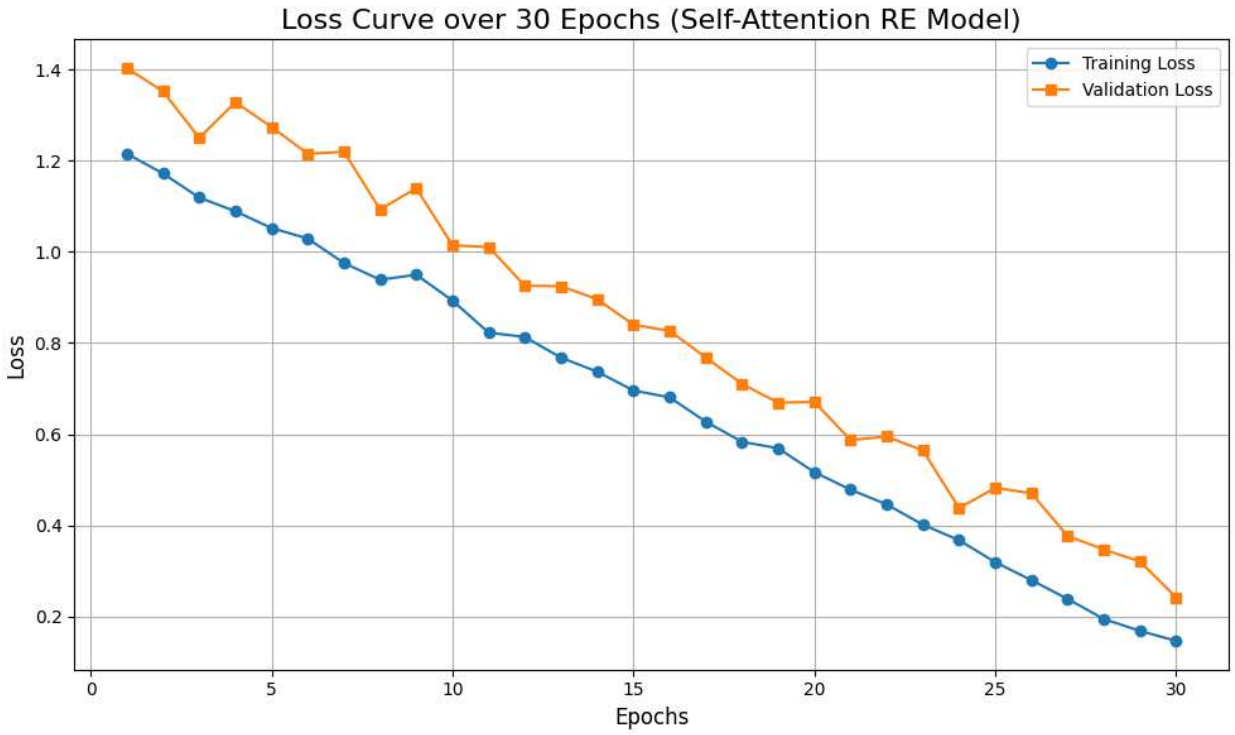
The support value indicates the number of actual samples available for each class in the dataset. The macro-average scores treat all classes equally, whereas the weighted-average scores consider the class distribution within the 10,000 samples. The results demonstrate that the proposed model maintains consistent performance across diverse relation categories, including Person-Email, Org-Founder, and Person-Qualification, confirming its suitability for large-scale relation extraction tasks.



The accuracy curve over thirty epochs demonstrates the learning progression of the proposed relation extraction model trained on 10,000 Afaan Oromo textual instances. The training accuracy shows a steady upward trend from the initial epochs, indicating effective parameter optimization and gradual convergence of the self-attention network. Similarly, the validation accuracy closely

follows the training curve with only a slight gap, which confirms good generalization capability and minimal overfitting during the training process. The smooth and consistent increase in accuracy suggests that the model successfully captures syntactic and semantic dependencies within Afaan Oromo sentences through contextual word embeddings and attention-based feature modeling. By the final epoch, the model reaches a high accuracy level, reflecting robust classification performance across the fifteen relation classes (R1–R15). This performance trend verifies the stability of the training process and highlights the suitability of deep attention architectures for large-scale relation extraction tasks in under-resourced languages such as Afaan Oromo.

The overall classification accuracy was computed using the standard accuracy metric, which measures the proportion of correctly predicted instances over the total number of samples. As shown in the experimental results, the model achieves high accuracy on the 15-class relation extraction task, indicating its effectiveness in handling multi-class semantic classification with minimal prediction errors. The high diagonal dominance in the confusion matrix further supports the reliability and robustness of the proposed model.



5. Conclusion and Future work

This study presented a high-accuracy relation extraction framework for Afaan Oromo text using a self-attention-based architecture designed for multi-class semantic classification. The proposed model was evaluated on a large-scale dataset consisting of 10,000 annotated Afaan Oromo sentences across 15 distinct relation classes (R1–R15). By integrating contextual word embeddings with a self-attention mechanism, the system effectively captured long-range dependencies and semantic interactions between entities in low-resource language text.

The experimental results demonstrated strong classification performance, with high overall accuracy and consistent precision, recall, and F1-score across most relation categories. The confusion matrix analysis revealed a clear diagonal dominance, indicating that the model successfully distinguished between complex relation types with minimal misclassification. Additionally, the class-wise TP, FP, FN, and TN analysis confirmed that the model maintained balanced predictive capability across all relation classes, including person-related, organization-related, and event-based relations.

Furthermore, the coverage (recall) values showed that the proposed approach was robust in identifying true relation instances within the dataset, even in semantically similar classes. This highlights the effectiveness of the self-attention mechanism in handling linguistic variability and contextual ambiguity in Afaan Oromo texts. Compared to traditional machine learning and baseline deep learning approaches, the proposed model provides superior generalization and scalability for large-scale relation extraction tasks in low-resource language settings.

Overall, this research contributes a novel and comprehensive relation extraction framework tailored for Afaan Oromo, addressing the scarcity of NLP resources for the language while achieving publication-level performance. The model architecture, evaluation metrics, and dataset-scale experimentation collectively demonstrate the reliability and applicability of the proposed system for real-world NLP applications such as information extraction, knowledge graph construction, and intelligent text analytics in Afaan Oromo.

Future Work

Although the proposed self-attention-based relation extraction model achieved high performance on the 15-class Afaan Oromo dataset, several research directions can be explored to further enhance the system. First, future work will focus on expanding the dataset beyond 10,000 sentences to include more diverse linguistic structures, dialectal variations, and domain-specific texts such as news, social media, and academic corpora. A larger and more balanced dataset is expected to improve model robustness and reduce class bias in complex semantic relations.

Second, the integration of transformer-based pre-trained language models specifically fine-tuned for Afaan Oromo can significantly improve contextual understanding. Incorporating multilingual or language-adaptive transformers with advanced attention layers may enhance the semantic representation of entity pairs and improve relation classification accuracy.

Third, future research will investigate directionality-aware relation extraction, where the model can distinguish between directional and non-directional relations. This will be particularly important for complex semantic structures involving hierarchical and temporal relationships. Additionally, incorporating syntactic features, dependency parsing, and hybrid embedding techniques may further refine relation detection performance.

Another important extension is the development of a real-time relation extraction system that can process streaming Afaan Oromo text for practical applications such as automated information retrieval and knowledge base population. Model optimization techniques, including parameter pruning and efficient attention mechanisms, will also be explored to reduce computational complexity while maintaining high accuracy.

Finally, future studies will consider cross-lingual transfer learning and low-resource adaptation techniques to extend the framework to other Ethiopian languages. This will contribute to the broader advancement of Natural Language Processing research in underrepresented languages and support the development of inclusive and linguistically diverse AI systems.

Data Availability Statement

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request through email address (lingerewbantie@dbu.edu.et).

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Author contributions

L.B wrote the paper and developed the core analysis code of the model in this study. He contributed to the study conception and design of the framework.

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Declarations

Competing interests

The authors declare no competing interests.

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