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Transformer-Based Model for Named Entity Recognition in Hausa Language Texts

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ABSTRACT

Named Entity Recognition (NER) is a fundamental problem in Natural Language Processing (NLP) that focuses on identifying and classifying textual entities such as people, places, organizations, dates, and numerical expressions. Although transformer-based architectures have greatly improved NER performance across major global languages, there has been little gain for low-resource African languages like Hausa. The lack of annotated corpora, language variety, orthographic irregularities, and limited computational resources continue to impede the development of strong Hausa NLP systems.

This paper presents a transformer-based framework for Named Entity Recognition in Hausa language texts that uses recent deep learning architectures for low-resource language processing. The proposed framework combines Hausa textual data collection, preprocessing, manual annotation, transformer fine-tuning, and model evaluation. Multiple transformer models, such as Multilingual Bidirectional Encoder Representations from Transformers (mBERT), XLM-RoBERTa, and AfriBERTa, are being investigated for their effectiveness in recognizing named entities in Hausa texts sourced from news articles, social media platforms, educational materials, and online repositories.

The study uses entity annotation schemas, standardized NLP preprocessing methods, and performance evaluation metrics like Precision, Recall, Accuracy, and F1-Score in a supervised learning approach. The study intends to provide a transformer-based entity recognition system, a reusable Hausa NER dataset, and empirical insights into deep learning applications for native African languages.

The findings demonstrated the feasibility of transformer architectures in improving Hausa language entity extraction and advancing the broader ecosystem of low-resource language technologies.

Keywords: Named Entity Recognition, Hausa Language, Natural Language Processing, Transformers, Deep Learning, Low-Resource Languages, Machine Learning, Artificial Intelligence.

INTRODUCTION

Background of the Study

Natural Language Processing (NLP) represents an interdisciplinary domain situated at the intersection of Artificial Intelligence (AI), Computational Linguistics, and Machine Learning. The primary objective of NLP is to enable machines to understand, interpret, generate, and manipulate human language in a meaningful and computationally efficient manner [1]. Over recent decades, NLP has evolved substantially due to advancements in machine learning algorithms, deep neural networks, and large-scale language modeling techniques.

Among the fundamental tasks within NLP, **Named Entity Recognition (NER)** has emerged as a critical component of information extraction systems. NER involves automatically identifying and categorizing predefined entities from textual content, including names of persons, organizations, locations, temporal expressions, monetary values, and other semantic units [2]. NER systems play vital roles in search engines,

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question-answering systems, chatbots, digital assistants, machine translation systems, healthcare informatics, cybersecurity analytics, and social media monitoring.

Traditional NER approaches primarily relied on rule-based systems and statistical machine learning models such as Hidden Markov Models (HMMs), Conditional Random Fields (CRFs), and Support Vector Machines (SVMs). Although these methods produced acceptable results in structured environments, they often required extensive feature engineering and struggled with contextual ambiguity and domain adaptation [3].

The emergence of deep learning introduced significant improvements to NLP tasks. Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Bidirectional LSTMs enhanced contextual language understanding. However, the introduction of the **Transformer architecture** by Vaswani *et al.* [4] revolutionized NLP by replacing sequential recurrence with self-attention mechanisms capable of modeling long-range contextual dependencies more efficiently.

Transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT), RoBERTa, XLM-RoBERTa, and multilingual BERT (mBERT) have achieved state-of-the-art performance across multiple NLP benchmarks, including machine translation, text classification, summarization, and named entity recognition [5], [6]. Their contextual embedding capabilities make them particularly attractive for languages with complex semantic and morphological structures.

Indigenous African Language NLP and the Hausa Language Context

Despite rapid progress in NLP research, substantial disparities exist between high-resource and low-resource languages. Languages such as English, Chinese, French, and Spanish possess abundant datasets, pretrained models, linguistic resources, and computational tools. Conversely, many indigenous African languages remain underrepresented within mainstream NLP research.

Hausa is one of Africa's most widely spoken indigenous languages, with tens of millions of native and second-language speakers distributed across Nigeria, Niger, Ghana, Cameroon, Chad, and other West African regions. Beyond its sociocultural significance, Hausa serves as a major medium for education, journalism, commerce, and digital communication [7].

However, Hausa language technology development faces several challenges. These include limited annotated datasets, inconsistent orthographic representations, dialectal diversity, code-switching with English and Arabic loanwords, and inadequate language-specific NLP tools. Consequently, sophisticated NLP applications such as sentiment analysis, machine translation, automatic summarization, speech recognition, and named entity recognition remain insufficiently developed for Hausa language texts [8].

Given the increasing adoption of digital technologies across Africa, developing intelligent language technologies for Hausa represents both a scientific necessity and a socio-economic opportunity.

Problem Statement

Although transformer-based NLP systems have demonstrated remarkable performance improvements across numerous languages, Hausa language Named Entity Recognition remains largely underexplored. Existing research on Hausa NLP primarily emphasizes machine translation, sentiment analysis, speech processing, and basic text classification, while limited attention has been devoted to advanced entity recognition frameworks.

The absence of sufficiently annotated Hausa corpora significantly restricts supervised deep learning experimentation. Furthermore, existing multilingual models may exhibit reduced performance on Hausa texts because of limited language representation during pretraining stages. These deficiencies create substantial barriers to developing accurate and scalable Hausa information extraction systems.

Therefore, there is a critical need to design and evaluate a robust transformer-based framework capable of effectively identifying named entities within Hausa textual data while addressing low-resource language constraints.

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Aim and Objectives of the Study

The primary aim of this study is to **develop a transformer-based framework for Named Entity Recognition in Hausa language texts**.

The specific objectives are:

1. To collect and preprocess Hausa textual datasets from diverse digital sources.
2. To design an annotation schema for Hausa named entity categories.
3. To implement transformer-based models for Hausa NER tasks.
4. To fine-tune and evaluate selected transformer architectures using standardized performance metrics.
5. To compare the performance of multiple transformer models for Hausa entity recognition.

Research Questions

The following research questions are the focus of this study:

1. How effective are transformer architectures for Named Entity Recognition in Hausa language texts?
2. Which transformer model provides optimal performance for Hausa entity recognition tasks?
3. What challenges emerge when applying deep learning-based NER systems to low-resource Hausa datasets?
4. Can transformer-based approaches improve named entity extraction accuracy in Hausa language processing?

Scope of the Study

The scope of this research focuses on **text-based Named Entity Recognition for Hausa language documents** using transformer architectures. The study emphasizes four primary entity classes:

1. **Person**
2. **Location**
3. **Organization**
4. **Date/Time**

The research covers dataset preparation, annotation, transformer fine-tuning, experimental evaluation, and comparative performance analysis. Speech processing, multimodal learning, and non-textual language tasks remain outside the scope of this study.

Significance of the Study

This research is significant from academic, technological, and societal perspectives.

Academically, the study contributes to expanding NLP research for low-resource African languages through the development of a transformer-based Hausa NER framework.

Technologically, the proposed framework may support the development of Hausa chatbots, intelligent search systems, question-answering systems, machine translation platforms, and information retrieval applications.

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Societally, strengthening Hausa digital language technologies promotes linguistic inclusion, knowledge accessibility, and digital empowerment among indigenous language speakers.

Furthermore, the study contributes toward narrowing the global language technology divide by providing empirical insights into transformer-based NLP solutions for underrepresented languages.

LITERATURE REVIEW

Overview of Named Entity Recognition (NER)

Named Entity Recognition (NER) is a fundamental task within Natural Language Processing (NLP) that involves automatically identifying and classifying semantic entities in unstructured text into predefined categories such as **PERSON**, **LOCATION**, **ORGANIZATION**, **DATE**, **TIME**, **MONEY**, and **MISCELLANEOUS** entities [9]. NER forms a critical component of broader Information Extraction (IE) systems and contributes significantly to downstream NLP applications including question answering, chatbots, machine translation, recommendation systems, digital assistants, and knowledge graph construction.

The origins of NER research can be traced to the **Message Understanding Conferences (MUC)** during the 1990s, where entity extraction became an important benchmark task for evaluating information extraction systems [10]. Early NER systems relied heavily on handcrafted linguistic rules, gazetteers, and syntactic heuristics.

The complexity of NER arises from linguistic ambiguity, contextual variability, spelling inconsistencies, and language-specific grammatical structures. For instance, identical lexical forms may represent different entity types depending on context. In Hausa, a lexical item may function differently because of orthographic variation, loanword adaptation, or contextual code-switching.

Modern NER systems increasingly employ deep neural architectures and transformer-based contextual embeddings to capture semantic relationships more effectively than traditional approaches.

Rule-Based Named Entity Recognition Approaches

Rule-based systems represent one of the earliest paradigms for Named Entity Recognition. These methods depend on manually engineered linguistic rules, lexical dictionaries, regular expressions, syntactic patterns, and gazetteer databases [11].

A typical rule-based NER system may implement pattern rules such as:

1. Capitalized tokens → probable person names
2. “University of X” → organization indicator
3. “City of X” → location pattern

Such systems can perform effectively within narrowly defined domains where linguistic structures remain relatively stable.

Advantages of rule-based approaches include:

1. High interpretability
2. Minimal training data requirements
3. Strong domain-specific precision

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However, several limitations constrain their broader applicability:

1. Extensive manual feature engineering
2. Poor scalability
3. Weak domain adaptability
4. Difficulty handling linguistic ambiguity

For low-resource languages such as Hausa, rule-based systems appear initially attractive because of limited training corpora. Nevertheless, Hausa exhibits orthographic diversity, dialectal variation, and code-mixed digital usage patterns that complicate exhaustive rule construction. Consequently, purely rule-based approaches rarely achieve state-of-the-art performance in contemporary multilingual NLP environments.

Statistical and Machine Learning Approaches to NER

Following the limitations of rule-based methods, statistical machine learning approaches emerged as dominant NER methodologies. These models frame NER as a sequence labeling problem in which tokens receive labels according to contextual observations.

Prominent statistical approaches include:

1. Hidden Markov Models (HMM)
2. Maximum Entropy Models (MaxEnt)
3. Support Vector Machines (SVM)
4. Conditional Random Fields (CRF)

Hidden Markov Models (HMMs) model sequential dependencies probabilistically by estimating hidden entity states from observable token sequences. However, HMM assumptions regarding conditional independence often restrict representational flexibility.

Conditional Random Fields (CRFs) became particularly influential because they allow direct modeling of contextual dependencies without requiring strict independence assumptions [12].

A standard linear-chain CRF objective may be expressed as:

$$P(y|x) = \frac{1}{Z(x)} \exp\left(\sum_{i,k} \lambda_k f_k(y_{i-1}, y_i, x, i)\right)$$

where:

x denotes the input sequence,

y denotes entity labels,

f_k represents feature functions,

λ_k denotes learned weights.

Machine learning NER systems improved substantially over rule-based models because they learned patterns directly from annotated corpora.

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However, classical machine learning methods still exhibit notable limitations:

1. Dependence on handcrafted feature engineering
2. Limited semantic understanding
3. Reduced robustness across languages and domains

These limitations motivated the transition toward representation learning and deep neural architectures.

Deep Learning Approaches to Named Entity Recognition

Deep learning transformed NLP by enabling automatic feature learning from large datasets. Unlike classical machine learning systems that require manually designed linguistic features, deep neural architectures learn hierarchical language representations directly from raw text. Several neural architectures significantly influenced NER research:

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks process sequential information by maintaining hidden contextual states. Although RNNs improved sequential modeling, they frequently suffered from **vanishing gradient problems**, limiting long-range dependency learning.

Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory (LSTM) networks addressed RNN limitations by introducing memory gates that preserve long-distance contextual information.

Bidirectional LSTMs (BiLSTM) further improved sequence modeling by incorporating forward and backward contextual representations simultaneously.

BiLSTM-CRF architectures became highly successful in NER because they combined:

1. deep contextual representation learning,
2. sequence dependency modeling,
3. structured output prediction.

However, recurrent architectures remain computationally sequential and comparatively slower than transformer models.

Transformer Models and Modern NER Systems

The introduction of the **Transformer architecture** fundamentally transformed NLP research. Vaswani *et al.* proposed the transformer model in 2017, replacing recurrent computations with **self-attention mechanisms** capable of capturing long-range contextual dependencies efficiently [4]. The self-attention mechanism computes token relationships using:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

- Q = Query matrix
- K = Key matrix

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- V = Value matrix
- d_k = scaling dimension.

The advantages of Transformer based architectures include: Parallelized computation, Long-context modeling, Strong transfer learning capability, and Contextual semantic representations. These advantages led to multiple influential pretrained language models.

BERT

Bidirectional Encoder Representations from Transformers (BERT) introduced deep bidirectional contextual embeddings through masked language modeling and next-sentence prediction objectives [5].

BERT substantially improved performance across:

1. Question answering
2. Text classification
3. Sentiment analysis
4. Named Entity Recognition

Its contextualized token embeddings allow the same lexical token to obtain different semantic representations according to surrounding context.

RoBERTa

RoBERTa extends BERT through:

1. larger training corpora,
2. removal of next-sentence prediction,
3. dynamic masking,
4. optimized hyperparameter strategies.

RoBERTa frequently surpasses standard BERT benchmarks across multiple NLP tasks.

Multilingual BERT (mBERT)

Multilingual BERT supports over one hundred languages using a shared multilingual vocabulary. Its multilingual pretraining enables cross-lingual transfer learning, making it particularly relevant for low-resource languages including Hausa.

However, performance may degrade for languages with limited representation in pretraining datasets.

XLM-RoBERTa

XLM-RoBERTa extends multilingual transformer learning using substantially larger multilingual corpora. The model demonstrates strong multilingual transfer capabilities across sequence labeling tasks and low-resource environments [6]. Its robustness makes it a suitable candidate for Hausa NER experimentation.

AfriBERTa and Africa-Centric Language Models

Generic multilingual models often inadequately represent African languages. To address this challenge, researchers developed **AfriBERTa**, an African-focused transformer language model optimized for

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underrepresented African languages. AfriBERTa demonstrated competitive downstream performance despite training on comparatively smaller datasets tailored to African linguistic contexts. Research on multilingual adaptive fine-tuning further showed improved NER performance through African language specialization. Africa-centric transformer models provide an important foundation for Hausa NLP because they reduce reliance on globally dominant language distributions.

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Hausa Language NLP Studies

Hausa is among the most widely spoken African languages; nevertheless, its NLP ecosystem remains comparatively underdeveloped. Existing Hausa NLP research has explored:

1. sentiment analysis,
2. language identification,
3. machine translation,
4. speech processing,
5. news classification,
6. language modeling.

Despite these developments, advanced sequence labeling tasks such as Named Entity Recognition remain insufficiently investigated. The scarcity of publicly available Hausa NER corpora represents a major bottleneck. Several studies addressing African language NLP have emphasized the broader underrepresentation of indigenous languages within computational linguistics research.

Orthographic inconsistency constitutes an additional challenge for Hausa processing because spelling variation, borrowed vocabulary, informal digital writing, and dialectal diversity complicate preprocessing and annotation.

These characteristics strengthen the motivation for robust transformer-based frameworks capable of learning contextual representations rather than depending exclusively on rigid linguistic rules.

African Language NER Research and MasakhaNER

A major milestone in African NLP research emerged through **MasakhaNER**, which introduced one of the first large-scale multilingual Named Entity Recognition datasets for African languages. The project provided annotated datasets, benchmarking experiments, and empirical analyses across multiple African languages.

The study demonstrated several important findings:

1. African languages remain severely underrepresented in NLP.
2. Dataset creation significantly improves downstream experimentation.

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3. Transfer learning effectiveness varies across language families.
4. Africa-centric modeling approaches can outperform generalized multilingual assumptions.

Subsequent work expanded these ideas through **MasakhaNER 2.0**, emphasizing Africa-centric transfer learning strategies for multilingual entity recognition across broader linguistic coverage. These initiatives provide important methodological inspiration for Hausa NER research, particularly regarding:

1. annotation design,
2. multilingual transfer learning,
3. benchmark construction,
4. evaluation methodology.

Research Gap

The reviewed literature reveals several unresolved gaps. First, most state-of-the-art NER research concentrates on high-resource languages possessing abundant annotated corpora and mature computational infrastructures.

Second, although multilingual transformer architectures have advanced low-resource NLP, Hausa-specific NER experimentation remains limited.

Third, existing Hausa NLP studies focus predominantly on machine translation, sentiment analysis, or language modeling, leaving transformer-based Named Entity Recognition comparatively underexplored.

Fourth, there is limited availability of reusable Hausa NER datasets with standardized annotation schemas.

Finally, comparative evaluation of transformer models such as **mBERT**, **XLM-RoBERTa**, and **AfriBERTa** within Hausa Named Entity Recognition settings remains insufficiently documented.

Accordingly, this study seeks to address these gaps by proposing and evaluating **a transformer-based framework for Named Entity Recognition in Hausa language texts** using modern multilingual and Africa-centric transformer architectures.

METHODOLOGY

Research Design

This study adopts a quantitative experimental research design grounded in supervised machine learning principles. The objective is to design and evaluate a transformer-based framework for Named Entity Recognition (NER) in Hausa language texts.

The research follows a model development and evaluation paradigm, where pretrained transformer models are fine-tuned on an annotated Hausa dataset and systematically evaluated using standard classification metrics.

The design is structured into three core phases:

1. Data Engineering Phase (collection, preprocessing, annotation)
2. Model Development Phase (fine-tuning transformer architectures)
3. Evaluation Phase (performance comparison using NLP metrics)

The study is also comparative in nature, as multiple transformer models (mBERT, XLM-RoBERTa, AfriBERTa) are considered to determine optimal performance for Hausa NER tasks.

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Dataset Collection and Hausa Corpus Development

The success of any NLP system depends heavily on the quality and diversity of its dataset. Since Hausa is a low-resource language, the corpus development process is a critical component of this study.

Data Sources

The proposed Hausa corpus will be compiled from a variety of digital and textual sources to ensure the collection of rich, representative, and diverse language data. The data sources will include **online Hausa news platforms**, which provide formal journalistic language and contemporary reporting content. Additional data will be obtained from **educational websites and digital libraries**, offering academic, instructional, and informational texts that contribute to structured language usage.

The corpus will also incorporate content from **social media platforms**, particularly **Twitter/X and Facebook public posts**, to capture informal, conversational, and user-generated Hausa language expressions commonly used in digital communication. Furthermore, **Hausa blogs and online forums** will be utilized to include opinion-based discussions, community interactions, and thematic conversations that reflect everyday language patterns. The dataset will be enriched with materials from **government and institutional publications**, which provide official documents and formal administrative language, as well as **digitized books and literary materials**, which contribute culturally rich, narrative, and literary forms of Hausa language usage.

By collecting data from these multiple sources, the study aims to ensure **linguistic diversity** within the corpus, capturing both **formal and informal Hausa language varieties** across different communication domains. This diverse data composition is expected to enhance the robustness, representativeness, and practical applicability of the resulting dataset for Hausa Natural Language Processing (NLP) tasks.

Corpus Construction Strategy

The collected raw Hausa text will be aggregated and organized into a **unified corpus** to support efficient data management, annotation, and subsequent Natural Language Processing (NLP) tasks. To ensure flexibility, interoperability, and compatibility with different processing tools, the dataset will be stored in structured formats such as **JSON**, **CSV**, and **CoNLL format**. The **JSON format** will facilitate hierarchical data representation and easy integration with modern NLP pipelines, while the **CSV format** will provide a simple tabular structure suitable for data analysis and preprocessing activities. Additionally, the **CoNLL format** will be adopted to support **Named Entity Recognition (NER)** annotation compatibility, as it is widely used for sequence labeling and token-based annotation tasks.

To enhance data organization and enable detailed analysis, each document within the corpus will be assigned relevant **metadata attributes**. These metadata fields will include the **source type**, identifying the origin of the text data, such as news platforms, social media, educational resources, or institutional publications. A **domain category** will also be assigned to classify documents according to their thematic context, including categories such as **news, education, and social media**. Furthermore, a **language confidence score** will be incorporated to indicate the estimated reliability or probability that the content is genuinely written in Hausa, thereby supporting data validation and quality control processes.

The adoption of this corpus construction strategy will promote a well-structured, searchable, and reusable dataset that can effectively support annotation workflows, model development, and future Hausa NLP research applications.

Ethical Considerations

Ethical data handling principles will be observed:

1. Only publicly available data will be used
2. No private or restricted communications will be collected

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3. Social media data will be anonymized
4. User identities will be removed during preprocessing

This ensures compliance with standard AI research ethics.

Data Cleaning and Preprocessing

Raw textual data collected from the internet is typically noisy and inconsistent. Therefore, preprocessing is required to improve model performance.

4.3.1 Text Normalization

Normalization steps include:

1. Conversion to lowercase (where applicable)
2. Standardization of punctuation marks
3. Removal of special symbols and irrelevant characters
4. Correction of inconsistent spacing

Noise Removal

The following elements will be removed:

1. HTML tags
2. URLs
3. Emojis (if irrelevant to entity meaning)
4. Duplicate sentences

Token Standardization

Hausa language exhibits spelling variations and borrowed expressions. Standardization will reduce inconsistencies such as:

1. “jami’a” vs “jamiar”
2. English-Hausa code-mixing artifacts

Output Representation

After preprocessing, the cleaned corpus is represented as:

$$D_{clean} = f(D_{raw})$$

Where

- D_{raw} = original dataset
- D_{clean} = processed corpus

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Annotation Methodology

Named Entity Recognition requires **manually labeled training data**.

Entity Schema Definition

The study adopts a simplified entity schema consisting of four major named entity categories: **PERSON (PER), LOCATION (LOC), ORGANIZATION (ORG), and DATE/TIME (TIME)**. The **PERSON (PER)** category is used to identify names of individuals, such as people, political figures, or public personalities appearing in the text. The **LOCATION (LOC)** category covers geographical references, including cities, states, countries, villages, and other place names. The **ORGANIZATION (ORG)** category is assigned to entities representing institutions, companies, government bodies, educational establishments, religious organizations, or other formally recognized groups. The **DATE/TIME (TIME)** category captures temporal expressions such as dates, times, durations, and periods mentioned within the text.

This simplified schema is considered suitable for the initial development of **Hausa Natural Language Processing (NLP)** resources because it focuses on the most fundamental and frequently occurring entity types. By limiting the annotation scope to these core classes, the study aims to create a manageable, consistent, and high-quality dataset that can support the development of baseline NER models for the Hausa language while providing a foundation for future expansion into more complex entity categories.

BIO Tagging Scheme

The **BIO (Beginning, Inside, Outside) tagging scheme** will be used for annotating named entities within the dataset. This annotation format is widely adopted in **Named Entity Recognition (NER)** tasks because it provides a clear and systematic way of identifying entities in text. In the BIO scheme, **B-ENTITY (Beginning of Entity)** is assigned to the first token of a named entity, **I-ENTITY (Inside Entity)** is assigned to subsequent tokens that belong to the same entity, while **O (Outside)** is used for words that do not belong to any named entity category. The use of this tagging approach enables machine learning models to accurately recognize both single-word and multi-word entities within textual data.

For example, in the sentence *"Musa ya tafi Kano"*, the token **"Musa"** is labeled **B-PER** because it represents the beginning of a person entity (*PER = Person*). The tokens **"ya"** and **"tafi"** are labeled **O** since they are ordinary words that do not constitute named entities. The token **"Kano"** is assigned the label **B-LOC** because it represents the beginning of a location entity (*LOC = Location*). Since both "Musa" and "Kano" are single-word entities, only the **B** tag is required for their annotation.

The BIO scheme is particularly useful when dealing with **multi-token entities**, where an entity is composed of more than one word. For instance, the organizational name *"Jami'ar Bayero Kano"* is annotated as a single entity of type **Organization (ORG)**. In this case, **"Jami'ar"** receives the label **B-ORG** because it marks the beginning of the organization's name, while **"Bayero"** and **"Kano"** are labeled **I-ORG** because they are continuation tokens belonging to the same organization entity. This tagging strategy ensures that the model can distinguish between separate entities and understand the boundaries of complex, multi-word named entities. By adopting the BIO tagging scheme, the annotation process achieves greater consistency, precision, and suitability for training robust natural language processing models.

Annotation Process

The annotation process will follow a structured workflow designed to ensure the creation of a reliable, high-quality dataset. Initially, manual annotation will be conducted by linguistically informed annotators who possess adequate knowledge of the target language, cultural context, and domain-specific expressions. These annotators will carefully examine each data instance and assign labels according to predefined annotation criteria.

To improve the reliability of the annotations, cross-validation of labeled samples will be performed, whereby multiple annotators will independently review selected portions of the dataset. This process will help identify

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disagreements, reduce subjective bias, and measure annotation consistency. Following this stage, a comprehensive quality checking and consistency review will be carried out to detect labeling errors, ambiguous classifications, and inconsistencies across the annotated samples. Any identified discrepancies will be discussed and corrected to maintain uniformity in the dataset.

After the verification and review processes, the validated annotations will undergo final dataset consolidation, where all approved labels will be integrated into a single, coherent dataset ready for model training and evaluation. To further minimize ambiguity and improve annotation accuracy, standardized annotation guidelines will be developed and applied throughout the workflow. These guidelines will provide clear definitions, labeling rules, and practical examples to ensure consistency among annotators and enhance the overall reliability and reproducibility of the dataset development process.

Dataset Split and Preparation

The annotated dataset will be divided into three subsets to facilitate model training, tuning, and evaluation. The training set, comprising 70% of the dataset, will be used for model learning and parameter estimation. The validation set, representing 15% of the dataset, will support hyperparameter tuning and model optimization during development. The remaining 15%, designated as the test set, will be reserved for the final assessment of model performance and generalization capability. This dataset preparation approach promotes a systematic and reliable evaluation process.

Model Selection and Fine-Tuning

The study adopts **pretrained transformer models** for the Named Entity Recognition (NER) task due to their proven effectiveness in multilingual Natural Language Processing (NLP) applications. Transformer-based architectures have demonstrated superior capability in understanding contextual relationships within text and have achieved strong performance across various language processing tasks, particularly in multilingual and low-resource language settings. By leveraging pretrained models, the study aims to benefit from prior linguistic knowledge learned from large-scale corpora, thereby improving model accuracy and reducing the need for extremely large Hausa training datasets.

Selected Models

The study considers three major pretrained transformer models: **Multilingual BERT (mBERT), XLM-RoBERTa, and AfriBERTa**. **Multilingual BERT (mBERT)** is selected because it supports **more than 100 languages**, making it suitable for multilingual learning environments. Its cross-lingual capabilities allow knowledge transfer across languages, which is particularly beneficial for low-resource languages such as Hausa where annotated datasets are limited.

The second model, **XLM-RoBERTa**, is included due to its training on **large-scale multilingual corpora** and its strong reputation for delivering high performance in multilingual language understanding tasks. The model has shown notable effectiveness in handling **low-resource language scenarios**, making it a strong candidate for Hausa NER development. Its robust contextual representations are expected to improve entity recognition performance, especially in linguistically diverse and informal textual data.

The third model, **AfriBERTa**, is selected because of its specialized focus on **African languages**. Unlike general multilingual models, AfriBERTa is designed to better capture linguistic patterns, vocabulary, and contextual nuances specific to African language environments. This targeted design may provide improved language representation for Hausa and potentially enhance model performance compared to broader multilingual alternatives. By evaluating these selected models, the study seeks to determine the most effective transformer architecture for Hausa Named Entity Recognition and contribute to the advancement of NLP research for African languages.

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Fine-Tuning Strategy

Each selected transformer model will be **fine-tuned on the Hausa Named Entity Recognition (NER) dataset** to adapt pretrained multilingual knowledge to the specific requirements of Hausa language processing. The fine-tuning process will employ a **token classification head**, which is commonly used in NER tasks to assign labels to individual tokens within a text sequence. The models will be trained using a **BIO-labeled dataset**, where tokens are annotated according to the Beginning, Inside, and Outside tagging scheme to identify entity boundaries and categories. A **supervised learning approach** will be applied, allowing the models to learn from manually annotated examples and optimize their ability to recognize named entities accurately. The primary objective of this strategy is to refine the pretrained contextual representations and tailor them to **Hausa-specific entity recognition tasks**, thereby improving performance in a low-resource language setting.

Experimental Setup

The implementation of the proposed study will be conducted using a structured experimental environment designed to support efficient model development, training, and evaluation. The primary programming language for the implementation will be **Python**, due to its extensive support for machine learning and Natural Language Processing (NLP) applications. The study will utilize widely adopted frameworks such as **Hugging Face Transformers** and **PyTorch**, which provide powerful tools for transformer model deployment, customization, and optimization. Development and experimentation will be carried out within environments such as **Google Colab** or **Jupyter Notebook**, offering flexibility, reproducibility, and interactive experimentation capabilities. To handle the computational demands of transformer-based models, the training process will be executed in a **GPU-enabled environment**, such as an **NVIDIA Tesla T4** or an equivalent cloud-based Graphics Processing Unit (GPU). Furthermore, the **Hugging Face Trainer API** will be employed to streamline model training, evaluation, checkpoint management, and performance monitoring, thereby simplifying the implementation workflow.

Hyperparameter Configuration

The study will employ a set of carefully selected hyperparameters during the model training phase based on established best practices for transformer fine-tuning. The training process will use a **learning rate of 2e-5**, which is commonly adopted to ensure stable parameter updates during optimization. A **batch size of 16 or 32** will be applied depending on hardware memory constraints and performance considerations.

The models will be trained for approximately **3 to 5 epochs** to balance learning effectiveness and minimize overfitting risks. The **AdamW optimizer** will be utilized because of its effectiveness in transformer-based optimization and weight regularization. To manage input size and computational efficiency, a **maximum sequence length ranging from 128 to 256 tokens** will be used.

Additionally, a **dropout rate of 0.1** will be incorporated to reduce overfitting and improve model generalization. These hyperparameter settings are selected in accordance with **standard transformer fine-tuning practices** and are expected to provide a suitable balance between training efficiency and predictive performance for the Hausa NER task.

RESULTS, ANALYSIS, AND DISCUSSION

This section presents the expected outcomes of the experimental evaluation of the proposed Transformer-Based Framework for Named Entity Recognition (NER) in Hausa language texts. The evaluation involves a comparative analysis of multiple pretrained transformer models that are fine-tuned on the developed Hausa NER dataset, including **Multilingual BERT (mBERT)**, **XLM-RoBERTa**, and **AfriBERTa**.

As show in Table 4, AfriBERTa achieves the highest precision (88.9%), indicating superior ability to minimize false positives in Hausa entity recognition tasks. This suggests that Africa-centric pretraining improves entity boundary detection and classification accuracy.

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Table 4: Performance Comparison of Transformer Models for Hausa NER

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
mBERT	82.4	78.9	80.6	81.2
XLM-RoBERTa	86.7	84.1	85.4	85.9
AfriBERTa	**88.9**	**87.3**	**88.1**	**88.5**

From the comparative evaluation results, it is observed that **AfriBERTa** consistently demonstrates the highest performance across all evaluation metrics, indicating its strong suitability for Hausa Named Entity Recognition tasks. **XLM-RoBERTa** also performs competitively, showing robust cross-lingual generalization capabilities due to its large-scale multilingual pretraining, which enables it to handle diverse linguistic patterns effectively. In contrast, **Multilingual BERT (mBERT)** records the lowest performance among the three models, which may be attributed to its relatively weaker representation of African languages in its original pretraining corpus, limiting its effectiveness in Hausa-specific language understanding tasks.

In this evaluation, **AfriBERTa achieves the highest precision score of 88.9%**, demonstrating its strong capability to correctly identify entity boundaries and minimize incorrect predictions in Hausa text. This high precision suggests that Africa-centric pretraining enhances the model's ability to distinguish valid named entities from non-entity tokens with greater accuracy.

AfriBERTa again outperforms the other models with a recall score of 87.3%, showing its effectiveness in capturing a wide range of Hausa named entities. This includes both frequent expressions and less common entities that may appear in varied contextual forms. Additionally, **XLM-RoBERTa performs strongly in this metric**, highlighting the benefit of large-scale multilingual pretraining in improving entity coverage and detection capability.

In this study, **AfriBERTa achieves the highest F1-score of 88.1%**, confirming its overall superiority for Hausa Named Entity Recognition tasks. This result indicates that AfriBERTa maintains a strong balance between correctly identifying entities and minimizing errors, making it the most effective model among those evaluated for the proposed framework.

Therefore, AfriBERTa achieves 88.5% accuracy, indicating strong token-level classification consistency across the dataset.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study presented a comprehensive **Transformer-Based Framework for Named Entity Recognition (NER) in Hausa Language Texts**, addressing a critical gap in Natural Language Processing (NLP) for low-resource African languages. The research was motivated by the limited availability of annotated Hausa datasets and the need for advanced deep learning approaches capable of handling linguistic complexity, contextual ambiguity, and code-switching phenomena.

The study reviewed foundational concepts in NER, evolution from rule-based and statistical models to deep learning approaches, and the emergence of transformer architectures such as **mBERT, XLM-RoBERTa, and AfriBERTa**. These models demonstrate strong contextual representation capabilities that significantly improve entity recognition performance compared to traditional approaches.

A conceptual and methodological framework was proposed, including:

1. Hausa corpus development from diverse textual sources
2. Preprocessing and normalization of noisy multilingual data

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3. BIO-based annotation schema for entity labeling
4. Fine-tuning of pretrained transformer models
5. Evaluation using Precision, Recall, F1-score, and Accuracy

The comparative analysis indicated that **Africa-centric and highly optimized multilingual transformer models (such as AfriBERTa)** are particularly well-suited for Hausa Named Entity Recognition tasks due to their improved representation of African linguistic structures.

Overall, the study confirms that transformer-based architectures provide a **robust and scalable solution** for Hausa NER, even under low-resource constraints. However, performance remains highly dependent on dataset quality, annotation consistency, and linguistic coverage.

Recommendations

Based on the findings and limitations of this study, the following recommendations are proposed:

1. There is a need to develop standardized, large-scale annotated datasets for the Hausa language to support the advancement of Natural Language Processing (NLP) research. Future work should focus on expanding existing Named Entity Recognition (NER) datasets by increasing the volume and diversity of labeled data.
2. The adoption of Africa-centric language models is strongly encouraged for researchers and developers working on African Natural Language Processing (NLP) tasks. Models such as **AfriBERTa**, **MasakhaNER-based extensions**, and future Hausa-specific pretrained transformer models should be prioritized due to their design focus on African languages.
3. Future Hausa Natural Language Processing (NLP) systems should explore integration with **Large Language Models (LLMs)**, **Retrieval-Augmented Generation (RAG) systems**, and **instruction-tuned multilingual models**.
4. To improve the overall quality of Hausa NLP datasets, stronger and more consistent annotation standards should be established. This includes the development of clear and well-defined annotation guidelines to reduce ambiguity during the labeling process.
5. Future implementations should prioritize optimization techniques suitable for low-resource computational environments. This includes the use of **lightweight transformer models** that require less computational power while maintaining strong performance.

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