

Bridging the Gap: Cross-Lingual Transfer Learning to Address Data Scarcity in Igbo Dialects for Machine Translation

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Abstract

Data scarcity and dialectal variation remain significant bottlenecks in developing robust Natural Language Processing (NLP) technologies for under-resourced languages. Igbo is a low-resource language in NLP due to a severe lack of high-quality digital corpora, annotated datasets, and specialised toolkits compared to dominant languages. This deficit hinders the development of basic AI tasks like machine translation and text summarisation. This paper seeks to bridge the gap between deep learning and sociolinguistic realities of Igbo by exploring cross-lingual transfer learning to address the challenges of data scarcity and dialectical variation within the context of Neural Machine Translation (NMT) for Igbo. By leveraging parameter sharing and large-scale multilingual pre-trained models, the data gap between standard and dialectal Igbo is bridged. The findings indicate that cross-lingual transfer significantly improves translation fidelity.

Keywords: Cross-Lingual Transfer Learning; Neural Machine Translation; Igbo Language; Low-Resource NLP; Dialectal Variation.

1. Introduction

1.1. The Problem

The "low-resource" challenge of Nigerian languages—where large speaker populations exist alongside a severe lack of digital parallel texts—hinders standard Neural Machine Translation (NMT). Without extensive, human-translated corpora, traditional NMT algorithms cannot effectively model syntax or semantic context, resulting in inaccurate, word-for-word translations (Nwoji and Abdyev, 2024; Ezeani et al., 2020; Inuwa-Dutse, 2025; Ekle and Das, 2025).

Since web data is heavily biased towards English and other high-resource languages, bridging the gap for Igbo requires moving beyond conventional web scraping. The field is addressing this through three main approaches (Inuwa-Dutse, 2025; Akwanya, 2025; Nwafor & Nguyen, 2025):

1. **Multilingual Transfer Learning:** AI models utilise linguistic similarities across larger datasets to improve translation.
2. **Multidialectal Datasets:** Researchers are actively developing comprehensive resources that encompass a variety of dialects and tones.
3. **Speech-to-Text Integration:** Organizations are mapping the multidialectal nature of Igbo directly from spoken traditions to feed algorithms.

These are the specific tools and datasets driving the shift:

1. **The IgboAPI Dataset:** An open-source, multidialectal Igbo-English dictionary and parallel text dataset (over 270,000 samples) designed to improve generalisation and dialect recognition in NMT (Emezue et al., 2024). It can be accessed on Hugging Face Papers.

2. **N-ATLaS:** An open-source, multilingual, and multimodal large language model launched by the Nigerian government. It is built on Meta's Llama-3 architecture and supports Igbo, Yoruba, Hausa, and Nigerian-accented English (Bilali, 2025; Punch, 2025).
3. **Lanfrica:** A centralised data hub designed specifically to solve the discoverability gap of African language resources, connecting researchers and data farmers to improve translation tools. Their datasets can be explored using Lanfrica Docs (Lanfrica).
4. **OkwuGbé:** A foundational Python library and deep neural network designed by researchers specifically for African low-resource languages, helping build Automatic Speech Recognition (ASR) models for Fon and Igbo (Dossou and Emezue, 2021).

1.2. Dialectal Variation

One of the biggest challenges in developing robust Natural Language Processing (NLP) tools for the Igbo language is that "Standard" or "Central" Igbo (based largely on Owerri and Umuahia) often lacks the specific phonology, tonal variations, and vocabulary found in satellite dialects like Awka, Nsukka, and Ikwo (Emezue et al., 2024; Nwoji and Abdyev, 2024). Overcoming this requires specialised datasets, and several resources and approaches are currently being developed and utilised in the AI and NLP communities (Emezue et al., 2024; Nkamigbo, 2011):

1. **Multi-Dialectal Datasets:** Researchers are actively building multi-dialectal corpora (such as the IgboAPI dataset) that pair English, Standard Igbo, and regional variants. This enables models to learn vocabulary substitutions and mapping systems between Standard Igbo and varieties such as Nsukka or Izii.
2. **Transfer Learning and Fine-Tuning:** Models like XLM-R and mBERT can be fine-tuned using specific, localised sentences or translation datasets for unseen dialects.
3. **Speech and Phonetic Models:** Models that process speech often struggle with Izii and Ezaa dialects, which have a richer phonological inventory (e.g., 9-10 vowels compared to the standard 8, and differing consonant systems). ASR (Automatic Speech Recognition) frameworks aim to train on localised audio data to map these unique phonetic and tonal markers.

1.3. The Solution

Transfer learning is a machine learning technique where a model, initially trained on a data-rich task or language, reuses its learned knowledge to perform a new, related task or understand a new, under-resourced language. Instead of starting from scratch, the model leverages previously learned linguistic patterns (Jain, 2025; Oroy and Danny, 2024; Refonte Learning, 2025).

Solving Data Scarcity

Many indigenous and regional languages lack the massive datasets (digitised text and speech) required to train modern AI. Transfer learning solves this data bottleneck by utilising knowledge from high-resource parent languages and broader African multilingual models in three core ways:

1. **Cross-Lingual Knowledge Transfer:** A model pre-trained on a high-resource language (like English or French) or a closely related parent language already grasps fundamental grammar, syntax, and sentence structure. When applied to an under-resourced African language, it transfers this structural understanding to perform tasks with little to no native training data (Thangaraj et al., 2024; Mahata et al., 2023; Schuster et al., 2019).
2. **Multilingual Adaptive Fine-Tuning (MAFT):** Multilingual models are pre-trained on hundreds of languages. By fine-tuning these models on even a small amount of high-quality data from a specific target language, the model updates its parameters to capture the unique vocabulary and cultural nuances of that language (Alabi et al., 2022).

3. **Leveraging Linguistic Shared Spaces:** Languages often share semantic meanings or phonological properties. Broad multilingual models—like AfriBERTa, AfroLID, or SERENGETI—act as a bridge. They map the shared concepts of thousands of languages into a unified mathematical representation, allowing knowledge to flow from a data-abundant language to a data-scarce one in the same language family (Adebara et al., 2023).

2. Related Work

2.1. Traditional Approaches

Rule-based and statistical machine translation (SMT) methods historically provided foundational, albeit rigid, approaches to English-to-Igbo translation. Though both struggled significantly with Igbo's complex dialects, tonal inflections, and rich idiomatic expressions, they were critical in building the initial computational frameworks for the language (Tonbara, 2025; Ayogu et al., 2018).

Rule-Based Machine Translation (RBMT)

RBMT systems relied on vast sets of handcrafted linguistic rules and bilingual dictionaries (Reverie, 2025; Ayogu et al., 2018).

1. **Mechanism:** The system analysed source English sentences, applied Igbo grammatical/syntactic structures, and synthesised the target text based on human-coded rules.
2. **Strengths:** Useful for enforcing specific grammatical constructs or handling highly structured terminology.
3. **Limitations:** Building the system required intensive, laborious input from linguistic experts. It struggled deeply with the contextual nuances, variations in dialects, and tonal dependencies inherent in the Igbo language (Agbeyangi et al., 2015; Comic, 2025).

Statistical Machine Translation (SMT)

SMT shifted away from manual rule-crafting, instead utilising large-scale parallel bilingual text corpora to deduce translation probabilities (Agbeyangi et al., 2015).

1. **Mechanism:** Phrase-based SMT (PB-SMT) models (such as those powered by the Moses toolkit) aligned phrases and words across English and Igbo to calculate the most statistically probable translation.
2. **Strengths:** Bypassed the need to manually write complex linguistic rules and yielded reasonable fluency within the specific, narrow domains it was trained on.
3. **Limitations:** SMT heavily depended on massive volumes of parallel text, which historically made it challenging for low-resource languages like Igbo. It frequently produced lexical and semantic errors when forced to handle long-distance word reordering or complex English-to-Igbo sentence mappings (Sreelekha, 2017; Ayogu et al., 2018).

2.2. NMT and Transfer Learning in Africa

Current literature in NaijaNLP focuses on bridging the digital divide for underresourced Nigerian languages through participatory research, multi-dialectal datasets (e.g., IgboAPI), and Africa-centric pre-trained language models (PLMs) (Ekwealor et al., 2026).

The IgboAPI

1. **Dialectal Variation:** The IgboAPI dataset is a multi-dialectal, audio-supported Igbo-English lexical database created to capture structural complexities across over 33 Igbo dialects.

2. **Data Scale:** It includes over 5,090 root words, nearly 18,000 dialectal word variations, and 27,800+ parallel example sentences.
3. **Practical Utility:** This dataset fuels tasks like Automatic Speech Recognition (ASR), machine translation, and spelling checkers, directly empowering local developer ecosystems like Igbo API (Emezue et al., 2024; Igbo API; Ekwonwune et al., 2026).

Projects Tackling Multilingual Pre-Training

1. **AfroXLMR & AfroBERT:** Rather than relying solely on high-resource languages, researchers have developed Africa-centric pre-trained models. Projects like AfroXLMR fine-tune massive multilingual models on localised African texts, drastically improving performance in Named Entity Recognition (NER) and Part-of-Speech tagging (Belay et al., 2025).
2. **MasakhaNER & MasakhaMT:** Championed by the Masakhane grassroots NLP community, these initiatives provide open-source NER and Machine Translation datasets across multiple African languages (including Hausa, Igbo, Yorùbá, and Naija Pidgin) (Zindi, 2021).
3. **Code-Mixed Sentiment Analysis:** Current literature emphasises creating dedicated sentiment analysis frameworks for Nigerian languages to handle complex phenomena like code-mixing, tonal variations, and morphological inflexion (Abdulyekeen and Abdullahi, 2026).

3. Methodology

3.1. Baseline Architecture

Foundational models bridge broad, pre-trained datasets to specialised downstream tasks using transfer learning. For multilingual applications, language-specific models have been engineered to address both data gaps and complex linguistic nuances (Belay et al., 2025; Educative, 2025).

Popular Multilingual and Specialised Foundation Models

1. **mBART (Multilingual Bidirectional and Auto-Regressive Transformer):**

A sequence-to-sequence denoising auto-encoder pre-trained on large-scale monolingual corpora across many languages. It pretrains the entire translation model directly by masking and reconstructing spans of text. As a result, it is highly effective for both text generation and machine translation tasks, eliminating the need to build models from scratch (Huggingface, 2020; Navarro and Casacuberta, 2023; Kalyan, 2022).

2. **AfroXLMR:**

A family of models adapted from the large-scale XLM-RoBERTa base specifically for African languages. It is created via Masked Language Model (MLM) adaptation. AfroXLMR covers dozens of languages from major African language families alongside high-resource languages (e.g., French, Arabic, English), making it a state-of-the-art encoder for Named Entity Recognition (NER), sentiment analysis, and subjective NLP tasks (Belay et al., 2025; Alabi et al., 2022).

3. **M2M (Many-to-Many):**

Introduced by Meta, this is a massively multilingual machine translation foundation model trained to translate between any pair of 100 languages directly. Unlike older, English-centric translation architectures, M2M was trained entirely on a multi-way corpus, enabling direct, high-quality translation flow between non-English languages (Kamboj et al., 2022; Boukil, 2021).

3.2. Cross-Lingual Transfer Process

The transfer learning pipeline for the Igbo language bridges the gap between massive, high-resource datasets and scarce, dialect-specific data by reusing learned linguistic structures. By starting with a model that already "understands" how language works, developers can achieve high performance on Igbo-specific tasks like translation or Named Entity Recognition (NER) with far less data than would be required to train from scratch (Jain, 2025).

1. Pre-training on High-Resource Corpora

The pipeline begins with pre-training, where a large neural network (typically a Transformer like mBERT or XLM-R) is exposed to massive, unlabelled datasets from "language-rich" sources like Wikipedia, CommonCrawl, or diverse multilingual collections (Chukwuneke et al., 2022).

- i. **Objective:** The model learns fundamental linguistic patterns, such as syntax, grammar, and semantic relationships between words.
- ii. **Knowledge Acquisition:** During this phase, the model internalises statistical regularities that are often universal across many languages.
- iii. **Initialisation:** This stage produces a "base model" with a set of weights that serve as a strong starting point for any specific language task (Brenndoerfer, 2025; Sy et al., 2024).

2. Adaptation to Low-Resource Languages

For a language like Igbo, which is classified as "low-resource" or "left-behind," direct pre-training is difficult due to a lack of digital data. Instead, the model leverages cross-lingual transfer learning, where knowledge from high-resource "parent" languages is transferred to the "child" language (Igbo) (Zoph et al., 2016; Emezue et al., 2024; Equalyz_AI, 2025).

Multilingual Embeddings: Models like AfriBERTa or XLM-R are often used because they were pre-trained on multiple languages simultaneously, allowing them to better represent African linguistic features (Equalyz_AI, 2025).

3. Fine-tuning on Dialect-Specific Igbo Datasets

The final stage is fine-tuning, where the pre-trained model is further trained on small, curated Igbo-specific datasets to adapt its general knowledge to the specific nuances of the language and its dialects (Nwafor & Nguyen, 2025; Weston, 2024; Subhasmukherjee, 2025; Omotoso et al., 2025).

Dataset Types

- i. **Bible Corpora:** Often used for their parallel nature (e.g., Igbo-English), providing a structured foundation for translation tasks.
- ii. **Igbo-English Dictionaries (e.g., IgboAPI):** Used to teach the model specific dialectal variations and specialised vocabulary, significantly improving its comprehension of diverse Igbo dialects.
- iii. **Annotated Data:** Small sets of human-labelled text (e.g., MasakhaNER) are used for specific downstream tasks like identifying names and locations in Igbo text.
- iv. **Process:** A task-specific layer (like a classification head) is often added to the top of the pre-trained model, and the entire system is updated using the smaller Igbo dataset at a low learning rate to avoid "forgetting" the general language knowledge it previously gained (Boujkian, 2025; Lin et al., 2023; Emezue et al., 2024; Chukwuneke et al., 2022).

The final model is a specialised version of the original "parent" model, now capable of high-accuracy performance in Igbo tasks despite the initial data scarcity (Liu et al., 2026; Emezue et al., 2024).

3.3. Data Augmentation

Data augmentation and synthetic data generation expand training pools without collecting new real-world data. These techniques prevent overfitting, correct class imbalances, and make machine learning models more robust by exposing them to diverse, varied examples (Murel and Kavlakoglu; Patil, 2026; Keskin, 2023).

1. Synthetic Data Generation

Synthetic data generation involves artificially creating new, plausible data points that mimic the statistical distribution of your original dataset (Experian, 2024).

- i.How it works: Instead of relying on real-world measurements or manual inputs, AI models (such as Large Language Models or Generative Adversarial Networks) generate fresh examples based on learned patterns.
- ii.Use Cases: It is incredibly valuable for privacy-preserving data (e.g., generating mock medical records) or training computer vision models where you need images of objects in varying lighting and angles.
- iii.Task Link: Explore automated pipelines using tools like Hugging Face Datasets (Vamsikd, 2025; Kili Technology, 2023; Artiba, 2025; Lyrz, 2024).

2. Back-Translation

Back-translation is a highly effective data augmentation technique specifically used in Natural Language Processing (NLP) and Machine Translation (Translated, 2026).

- i.How it works: A text sample is translated into a target language (e.g., English to French) and then immediately translated back to the original source language (French back to English).
- ii.The Benefit: Because of slight nuances and losses in translation, the final output reads as a natural paraphrase of the original text, providing a brand-new training example while completely preserving the original meaning.
- iii.Task Link: This can be easily implemented using popular NLP libraries like NLPAUG documentation to test text augmentations (Rosvall, 2023; Joshi et al., 2023; Translated, 2026).

3. Other Key Techniques

Depending on the project type, data expansion relies on targeted transformations:

For Text (NLP) (Talby, 2024; Nayak, 2020; Feng et al., 2024):

- i.**Synonym Replacement:** Replacing random words with their synonyms to create varied sentence structures.
- ii.**Random Insertion/Deletion:** Randomly adding or removing non-critical words to teach the model how to handle incomplete or conversational data.
- iii.**Templatic Augmentation:** Using set templates with swapped-out variables to generate massive datasets for specific intents.

For Images (Computer Vision) (Unidata, 2026; John, 2024; Lightly, 2026):

- i.Geometric Transformations: Flipping an image horizontally, rotating it, cropping it, or scaling it.

- ii. Colour Space Augmentation: Adjusting the brightness, contrast, or saturation to simulate different weather conditions or lighting.

While expansion is highly beneficial, synthetic generation and back-translation can sometimes amplify or replicate existing biases present in the seed data. It is critical to curate and filter augmented datasets to maintain high quality.

4. Discussion

Cross-lingual transfer learning addresses the critical data scarcity in underrepresented Igbo dialects by enabling machine translation (MT) models trained on high-resource languages (or standard Central Igbo) to learn the patterns of marginalised regional dialects. This technology mitigates data gaps and democratises digital access for diverse Igbo-speaking communities (Emezue et al., 2024).

Sociolinguistic Impacts on the Igbo Language

1. Mitigation of Linguistic Inequality

Without technological intervention, dialects with few digital resources—such as Owerri, Ngwa, Enuani, or Awka—risk marginalisation or obsolescence compared to globally standardised or dominant languages. Cross-lingual transfer bridges this digital divide, allowing AI systems to interpret and produce local dialects. This brings digital equity to the speech communities of Southeastern Nigeria (Mbey et al., 2025; Idris et al., 2026; Emezue et al., 2024).

2. Shift in Language Standardisation and Prestige

Historically, Central Igbo has dominated written literature and formal education. Dialect-aware MT tools challenge this power dynamic by assigning digital prestige to regional dialects. When native speakers see their specific dialect recognised by AI, it fosters a renewed sense of linguistic pride and encourages everyday digital communication in their mother tongue (Olojo et al., 2025; Obiwuru and Onwuegbule, 2025).

3. Balancing Globalisation and Localisation

Machine translation inherently interfaces with global languages, primarily English. While MT makes Igbo more accessible, it poses a risk of losing cultural and grammatical nuances if models prioritise literal translations over contextual meaning. The sociolinguistic challenge lies in ensuring that these tools respect local idioms, proverbs, and ecological references rather than applying an Anglicised syntax to Igbo speech (Olojo et al., 2025; Obiwuru and Onwuegbule, 2025).

How This Technology Preserves Regional Dialects

1. Automated Documentation and Lexicon Building

Cross-lingual transfer facilitates quick dialectal corpus creation. By utilising datasets like IgboAPI, models can analyse audio or text embeddings and initiate semantic tagging without the need for extensive parallel datasets for every local variant. This allows for immediate digital recording of fading slang, folk tales, and regional lexicons (Emezue et al., 2024).

2. Educational Empowerment and Intergenerational Transfer

The primary driver of language endangerment is the lack of intergenerational transmission, particularly among youths in urban centres. Dialect-inclusive MT tools can be integrated into educational apps and smart keyboards. This empowers

learners to explore regional dialects in an interactive, engaging format, compensating for the scarcity of qualified mother-tongue teachers in certain areas (Emeka-Nwobia, 2019; Mbey et al., 2025).

3. Enhancing Conversational AI

By combining transfer learning with automatic speech recognition, developers can build conversational AI agents capable of understanding localised dialects in real-time. This dynamic keeps minority dialects functionally relevant in the modern digital age, proving to native speakers—especially the youth—that their ancestral vernacular can fully participate in contemporary communication.

Training and maintaining Large Language Models (LLMs) for Igbo presents four interconnected challenges: high computational costs, tokenisation complexities, catastrophic forgetting, and dialect dilution. Addressing these limitations is essential for ensuring digital equity and linguistic accuracy (Asprovskas and Hunter, 2024; Okafor, 2025).

5. Conclusion and Future Work

Transfer learning is a highly effective solution for data-scarce indigenous languages, overcoming the severe data limitations they face. By leveraging pre-trained models from high-resource languages, algorithms adapt to target indigenous languages using minimal data. This approach achieves high performance in machine translation and semantic understanding without needing massive, expensive, original datasets.

To bridge the digital language gap and ensure accurate, localised dialect representation in AI, researchers should adopt a community-centric participatory framework. This includes using native speakers to crowdsource localised texts and leveraging advanced foundational models to scale these efforts.

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