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Decolonizing the Archive: Applying Natural Language Processing to Identify Linguistic Bias in Colonial Historical Records

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ABSTRACT

Colonial historical archives represent valuable sources of information about political systems, cultural practices, social structures, indigenous communities, and historical transformations. However, these records frequently contain linguistic biases shaped by colonial ideologies, administrative hierarchies, racial classifications, and Eurocentric perspectives. Such biases influence how historical events, indigenous populations, and marginalized communities are described, categorized, and interpreted. The present study explores the application of Natural Language Processing (NLP) techniques to identify, analyze, and evaluate linguistic bias within colonial historical records as a step toward decolonizing digital archives. The proposed approach integrates advanced computational text analysis, sentiment analysis, named entity recognition, topic modeling, word embeddings, and contextual language models to detect discriminatory terminology, unequal representations, stereotypical descriptions, and patterns of linguistic exclusion. By examining historical texts across different periods and administrative contexts, the study aims to identify how colonial narratives systematically shaped the representation of indigenous identities, cultural traditions, and social relationships.

Furthermore, it proposes a bias-aware analytical framework that combines computational methods with historical scholarship, critical discourse analysis, and indigenous knowledge perspectives to improve interpretative accuracy. Particular attention is given to the challenges of historical language variation, outdated terminology, multilingual documentation, incomplete metadata, and the risk of reproducing existing biases through automated NLP systems. The study emphasizes that computational identification should complement rather than replace human interpretation and contextual historical analysis. Ultimately, this research highlights the potential of NLP as a methodological tool for exposing hidden ideological structures in colonial documentation, promoting inclusive historical interpretation, and supporting the ethical transformation of digital archival practices. It contributes to the broader development of digital humanities by establishing a framework for critically examining historical language and advancing more equitable, transparent, and culturally responsive archival research.

Keywords: Decolonization of Archives, Natural Language Processing (NLP), Linguistic Bias Detection, Colonial Historical Records, Digital Humanities

INTRODUCTION

Historical archives serve as essential repositories of collective memory, cultural identity, political developments, and social transformations. They preserve historical documents, administrative reports, personal correspondence, government records, missionary publications, travel narratives, and other written materials that provide valuable insights into past societies. However, colonial historical archives are not neutral representations of historical reality. Many were created, organized, and maintained by colonial administrations whose political interests, cultural assumptions, and ideological perspectives significantly influenced the language and narratives contained within them. Consequently, colonial records frequently reflect Eurocentric interpretations, racial hierarchies, cultural stereotypes, and unequal power relationships. These linguistic patterns have shaped historical scholarship and continue to influence how indigenous communities, colonized populations, and marginalized groups are represented in contemporary knowledge systems.

The concept of decolonizing the archive emphasizes the need to critically examine historical documentation, challenge colonial interpretations, and incorporate perspectives that have traditionally been excluded or misrepresented. Colonial administrators often employed specific linguistic expressions to classify indigenous populations, describe cultural practices, establish social hierarchies, and justify political authority. Terms associated with civilization, primitiveness, development, obedience, rebellion, and cultural superiority were frequently used to construct distinctions between colonizers and colonized populations. Such expressions were not merely descriptive; they frequently reflected broader ideological assumptions that legitimized colonial governance and reinforced unequal social relationships. Therefore,

identifying linguistic bias within historical records is essential for developing more inclusive, balanced, and historically responsible interpretations.

Traditional approaches to examining linguistic bias primarily depend on qualitative historical analysis, critical discourse analysis, archival interpretation, and comparative textual examination. Although these methods provide valuable contextual understanding, they can become time-consuming when researchers investigate extensive archival collections containing thousands of documents across multiple languages and historical periods. The increasing digitization of historical materials has created opportunities to apply computational techniques to large-scale archival research. In this context, Natural Language Processing (NLP) offers promising methods for systematically identifying linguistic patterns, evaluating word usage, recognizing historical entities, and examining the representation of different social and cultural groups.

Natural Language Processing is a branch of artificial intelligence that enables computers to analyze, interpret, and process human language. Techniques such as sentiment analysis, named entity recognition, topic modeling, semantic analysis, word embeddings, and transformer-based language models can support the identification of potentially biased linguistic expressions in historical documents. For example, sentiment analysis can help examine differences in the descriptions of colonial administrators and indigenous populations, while named entity recognition can identify how individuals, communities, geographical locations, and institutions are represented. Topic modeling can reveal recurring colonial narratives, whereas semantic analysis can identify associations between particular social groups and stereotypical or discriminatory terminology.

PROPOSED MODELS AND METHODOLOGIES

The proposed study, “Decolonizing the Archive: Applying Natural Language Processing to Identify Linguistic Bias in Colonial Historical Records,” develops an interdisciplinary computational framework for detecting, classifying, and interpreting linguistic bias in historical colonial documents. The methodology integrates Natural Language Processing (NLP), machine learning, deep learning, historical linguistics, and critical discourse analysis to examine how colonial ideologies are reflected in archival language. The proposed framework aims to identify discriminatory terminology, stereotypical descriptions, unequal representations, and patterns of linguistic exclusion while preserving the historical and cultural context of archival materials.

2.1 Research Design and Methodological Framework

The research adopts a mixed-method approach combining quantitative computational analysis with qualitative historical interpretation. Quantitative methods are used to identify recurring linguistic patterns and measure potential bias, whereas qualitative methods examine the historical meanings and ideological implications of the identified expressions.

The proposed methodology consists of the following stages:

1. Historical archival data collection.
2. Digitization and text extraction.
3. Historical text preprocessing and normalization.
4. Linguistic bias identification.
5. NLP-based classification and semantic analysis.
6. Comparative analysis of colonial and indigenous representations.
7. Human validation and historical interpretation.

This integrated methodology ensures that computational findings are evaluated within their appropriate historical, political, and cultural contexts.

2.2 Historical Archival Data Collection

The first stage involves collecting digitized colonial historical records from libraries, museums, government repositories, historical databases, and digital archival platforms.

Potential data sources include:

- Colonial administrative reports and government correspondence.
- Census records and population surveys.
- Missionary publications and travel narratives.
- Military and judicial documents.
- Colonial newspapers and official gazettes.
- Historical ethnographic studies.
- Indigenous accounts and translated historical narratives.

The collected documents may cover different geographical regions, colonial administrations, languages, and historical periods. Metadata such as publication year, author identity, document category, geographical origin, and institutional source will be recorded to support contextual analysis.

2.3 Text Extraction and Historical Text Preprocessing

Historical documents are frequently available as scanned images or poorly structured digital texts. Optical Character Recognition (OCR) technology will therefore be used to convert scanned archival materials into machine-readable text.

The preprocessing stage will include:

- OCR correction: Identifying and correcting errors generated during text recognition.
- Text normalization: Standardizing inconsistent spelling conventions while retaining original forms.
- Tokenization: Dividing documents into individual words, sentences, and meaningful linguistic units.
- Stop-word handling: Removing irrelevant linguistic elements where appropriate.
- Lemmatization: Converting words into their basic grammatical forms.
- Historical vocabulary preservation: Maintaining outdated expressions and historically significant terminology for contextual interpretation.
- Language identification: Recognizing multilingual documents and language variations.

Special attention will be given to preserving historically meaningful expressions because excessive normalization may eliminate the very linguistic evidence that the study intends to investigate.

2.4 Dictionary-Based Linguistic Bias Detection Model

The first proposed model uses a historically contextualized linguistic dictionary to identify potentially discriminatory or ideologically loaded expressions.

The dictionary will contain categories such as:

1. Racial and ethnic stereotyping.
2. Cultural superiority and inferiority.
3. Civilizational classifications.
4. Religious and cultural discrimination.
5. Colonial administrative terminology.
6. Language associated with resistance and rebellion.
7. Gender-based and social hierarchies.

The system will compare archival vocabulary against these categories to identify potentially biased expressions.
A basic bias-frequency measure can be represented as:
\[BF=\frac{N_b}{N_t}\times 1000 \]

Where:

- \(BF\) = Bias frequency per 1,000 words.
- \(N_b\) = Number of identified potentially biased expressions.
- \(N_t\) = Total number of words in the document.

This measure will help compare the frequency of potentially biased language across different documents and historical periods. However, frequency alone will not establish discriminatory intent; contextual examination will remain necessary.

2.5 Machine Learning-Based Bias Classification Model

A supervised machine learning model will be developed to classify sentences and paragraphs according to their linguistic characteristics.

Potential classification categories include:

- Neutral or descriptive language.
- Racially biased language.
- Culturally discriminatory language.
- Colonial ideological language.
- Stereotypical representation.
- Politically or administratively prejudiced language.

The proposed machine learning algorithms include:

A. Support Vector Machine (SVM): Used to classify historical text based on linguistic features, including TF-IDF representations and selected contextual indicators.

B. Random Forest: Applied to identify complex relationships between vocabulary patterns, document characteristics, and bias categories.

C. Logistic Regression: Used as an interpretable baseline classifier for distinguishing potentially biased and neutral expressions.

The training dataset will be manually annotated by researchers with relevant historical and linguistic expertise. Inter-annotator agreement will be evaluated to improve annotation reliability.

RESULTS & ANALYSIS

The proposed study, "Decolonizing the Archive: Applying Natural Language Processing to Identify Linguistic Bias in Colonial Historical Records," examines the potential of Natural Language Processing (NLP) techniques to identify linguistic bias, discriminatory expressions, cultural stereotypes, and unequal representations within colonial historical documentation. The analysis focuses on how computational methods can reveal patterns of colonial ideology embedded in historical texts and support more inclusive interpretations of archival materials.

Since this study proposes a computational framework rather than reporting a completed empirical experiment, the results presented below are anticipated analytical outcomes and illustrative values, not measurements obtained from an actual archival dataset.

3.1 Identification of Linguistic Bias in Colonial Records

The proposed dictionary-based and machine learning models are expected to identify different categories of linguistic bias in colonial historical documents. These categories include racial stereotyping, cultural discrimination, civilizational superiority, administrative prejudice, and the negative representation of indigenous communities.

The analysis is expected to demonstrate that colonial administrative reports, missionary publications, census records, and ethnographic narratives contain different patterns of potentially biased language.

For example, certain colonial documents may describe indigenous populations through expressions associated with dependency, primitiveness, disorder, or resistance, while colonial institutions may be represented through terminology associated with authority, governance, civilization, and progress.

Such differences can reveal how linguistic choices contributed to the construction and reinforcement of colonial power relationships.

3.2 Comparative Performance of NLP Models

The proposed machine learning and deep learning models will be evaluated using accuracy, precision, recall, and F1-score. The following table provides illustrative target performance values to demonstrate how the models may be compared during empirical validation.

NLP Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	79.5	78.2	76.8	77.5
Support Vector Machine	84.2	83.1	82.4	82.7
Random Forest	81.6	80.4	79.2	79.8
BERT	90.3	89.7	88.9	89.3
RoBERTa	92.1	91.4	90.8	91.1
Multilingual BERT	88.6	87.9	86.5	87.2

Note: All numerical values are hypothetical and intended solely for illustrating the proposed evaluation framework.

The anticipated comparison suggests that transformer-based models such as RoBERTa and BERT may achieve better classification performance than traditional machine learning approaches because they can capture contextual relationships between words and sentences.

However, their actual performance will depend on training data quality, historical language coverage, annotation consistency, and domain adaptation.

3.3 Analysis of Major Linguistic Bias Categories

The proposed framework will classify potentially biased expressions into several thematic categories. The following illustrative distribution represents a possible analytical outcome.

Linguistic Bias Category	Illustrative Distribution (%)
Racial and Ethnic Stereotyping	26
Cultural Superiority and Inferiority	22
Colonial Administrative Prejudice	19
Religious and Cultural Discrimination	14
Gender and Social Hierarchies	11
Political and Resistance-Related Bias	8
Total	100

The illustrative distribution indicates that racial and ethnic stereotyping and cultural superiority narratives may represent important areas of investigation in colonial archival language.

These patterns can help researchers examine how historical descriptions established distinctions between colonial authorities and indigenous populations. Nevertheless, the actual distribution must be established through document-level annotation and computational analysis.

3.4 Sentiment Analysis of Colonial and Indigenous Representations

Sentiment analysis is expected to reveal differences in the evaluative language used to describe colonial authorities and indigenous communities.

The proposed analysis will compare positive, negative, and neutral linguistic expressions across different archival categories.

Representation Category	Positive Language (%)	Negative Language (%)	Neutral Language (%)
Colonial Administrators	48	17	35
Indigenous Communities	19	51	30
Colonial Institutions	52	16	32
Indigenous Cultural Practices	24	43	33

Note: Illustrative values only; they do not represent verified historical findings.

The hypothetical distribution demonstrates how sentiment analysis could reveal unequal evaluative patterns in colonial narratives. For example, colonial institutions might receive comparatively favorable descriptions, whereas indigenous cultural practices might be described through negative or dismissive expressions.

Such findings would require contextual validation because sentiment polarity does not automatically indicate ideological prejudice. Historical quotations, reported speech, irony, and critical commentary can significantly influence sentiment classification.

3.5 Topic Modeling and Colonial Narrative Identification

Topic modeling techniques such as Latent Dirichlet Allocation (LDA) and BERTopic will be used to identify recurring themes within archival documents.

The expected analysis may reveal the following major thematic areas:

1. Colonial Governance: Administrative authority, taxation, law enforcement, and institutional control.
2. Civilization and Cultural Hierarchy: Representations of European cultural superiority and indigenous traditions.
3. Religious and Missionary Activities: Religious conversion, cultural transformation, and missionary influence.
4. Economic Exploitation: Land ownership, agricultural production, taxation, and labor relations.
5. Indigenous Resistance: Rebellion, political opposition, cultural preservation, and anti-colonial movements.
6. Education and Social Reform: Colonial educational systems and the representation of indigenous knowledge.

The identification of these themes can help researchers understand how colonial institutions organized historical narratives and which subjects received greater documentary attention.

COMPARATIVE ANALYSIS IN TABULAR FORM

The comparative analysis of “Decolonizing the Archive: Applying Natural Language Processing to Identify Linguistic Bias in Colonial Historical Records” evaluates different computational approaches and traditional historical research methods for identifying linguistic bias in colonial archival documents. The comparison focuses on classification

accuracy, contextual understanding, semantic analysis, scalability, multilingual capabilities, interpretability, and historical reliability.

4.1 Comparative Analysis of NLP Models

NLP Model	Major Technique	Key Strength	Major Limitation	Application
Logistic Regression	Statistical classification	Simple and interpretable	Limited contextual understanding	Basic bias classification
Support Vector Machine	Supervised learning	Effective text classification	Depends on feature engineering	Discriminatory terminology detection
Random Forest	Ensemble learning	Handles complex feature relationships	Limited semantic understanding	Linguistic pattern recognition
BERT	Transformer architecture	Contextual language understanding	Computationally demanding	Context-sensitive bias detection
RoBERTa	Optimized transformer	Strong contextual representations	Requires suitable training data	Colonial narrative classification
Multilingual BERT	Multilingual transformers	Supports multiple languages	Uneven language performance	Multilingual archival analysis
LDA	Probabilistic topic modeling	Identifies recurring themes	Limited contextual interpretation	Colonial discourse identification
BERTopic	Transformer-based topic modeling	Semantic topic identification	Sensitive to clustering and parameter choices	Historical narrative analysis

4.2 Comparative Analysis of Bias Detection Techniques

Evaluation Criteria	Dictionary-Based Analysis	Machine Learning	Deep Learning	Human Expert Analysis
Vocabulary Identification	High	High	High	High
Contextual Understanding	Low	Moderate	High	Very High
Historical Interpretation	Limited	Limited	Variable	Very High
Scalability	High	High	High	Low
Semantic Relationship Analysis	Low	Moderate	High	High
Multilingual Processing	Dictionary-dependent	Dataset-dependent	Model-dependent	Expertise-dependent
Interpretability	High	Moderate	Variable	High
Computational Requirements	Low	Moderate	High	Low
Bias Detection Reliability	Context-dependent	Training-dependent	Training-dependent	Expertise-dependent

4.3 Comparative Analysis of Colonial and Indigenous Representations

Analytical Dimension	Colonial Representation	Indigenous Representation	Research Objective
Cultural Identity	Frequently described through colonial classifications	Often documented through external descriptions	Identify cultural stereotyping
Social Structure	Evaluated through colonial administrative frameworks	Frequently represented as traditional or hierarchical	Examine unequal social representation
Religious Practices	Sometimes presented as a basis for cultural intervention	Frequently described through missionary perspectives	Identify religious discrimination
Political Activities	Often associated with governance and authority	Sometimes characterized through rebellion or resistance	Examine political linguistic bias
Economic Activities	Associated with administration and commercial development	Often discussed through labor and resource extraction	Identify economic power narratives
Education	Frequently linked with colonial institutional reform	Indigenous knowledge systems may receive limited attention	Examine educational representation

4.4 Comparative Analysis of Traditional and Computational Approaches

Parameters	Traditional Archival Research	NLP-Based Archival Research	Proposed Integrated Framework
Research Method	Manual examination	Automated text analysis	Hybrid methodology
Data Collection	Archival investigation	Digitized text collection	Historical archival integration
Text Processing	Manual reading	OCR and NLP preprocessing	OCR with expert correction
Linguistic Analysis	Qualitative interpretation	Computational classification	Contextual computational analysis
Bias Identification	Researcher interpretation	Algorithmic detection	Automated detection and validation
Narrative Analysis	Critical discourse analysis	Topic modeling	Combined discourse and topic analysis
Historical Context	Strong	Often limited	Strong through expert validation
Research Scalability	Limited	High	High
Reliability	Depends on researcher expertise	Depends on data and model quality	Improved through interdisciplinary validation

4.5 Comparative Analysis of Performance Evaluation Metrics

Performance Metric	Purpose	Importance in the Proposed Study
Accuracy	Measures overall classification correctness	Evaluates general model performance
Precision	Measures correctness of predicted biased passages	Reduces false accusations of bias
Recall	Measures the identification of actual biased passages	Helps identify overlooked linguistic bias
F1-Score	Combines precision and recall	Provides balanced evaluation
Macro-F1	Calculates average F1 across categories	Addresses class imbalance
Confusion Matrix	Identifies classification errors	Reveals category-specific weaknesses
Cohen's Kappa	Measures agreement between annotators	Evaluates annotation consistency
Cross-Language Evaluation	Tests performance across languages	Assesses multilingual reliability

LIMITATIONS & DRAWBACKS

Although Natural Language Processing (NLP) offers significant opportunities for identifying linguistic bias in colonial historical records, its application involves several technical, methodological, historical, and ethical limitations. Colonial archives contain complex linguistic structures, outdated terminology, culturally specific expressions, and historically influenced narratives that cannot always be accurately interpreted through automated computational systems. The proposed framework combines machine learning, deep learning, semantic analysis, and historical interpretation; however, its effectiveness depends on data quality, model reliability, contextual understanding, and expert validation.

5.1 Limitations of Historical Language Understanding

One of the major challenges is the interpretation of historical vocabulary. Colonial documents frequently contain archaic expressions, outdated grammatical structures, obsolete terminology, and words whose meanings have changed over time.

Modern NLP models may incorrectly interpret these expressions because they are generally trained on contemporary linguistic datasets. Consequently, historically significant terminology may be classified incorrectly or lose its original cultural meaning.

5.2 OCR Errors and Poor Archival Data Quality

Many colonial historical records exist as handwritten manuscripts, damaged documents, faded photographs, and poorly scanned archival materials. Optical Character Recognition (OCR) systems may produce inaccurate text extraction.

Major problems include:

- Incorrect recognition of historical characters.
- Missing or duplicated words.
- Inconsistent spelling and punctuation.
- Damaged or incomplete documents.
- Poor-quality multilingual text recognition.

These errors can negatively affect subsequent NLP analysis and reduce classification accuracy.

5.3 Limited Availability of Annotated Historical Datasets

Supervised machine learning models require appropriately labeled datasets for training and evaluation. However, large-scale annotated datasets specifically designed for identifying linguistic bias in colonial historical records remain a significant research challenge.

The absence of standardized historical annotations creates difficulties in:

- Training reliable classification models.
- Comparing results across different archival collections.
- Evaluating model generalization.
- Establishing consistent linguistic bias categories.
- Developing historically representative training datasets.

5.4 Contextual Interpretation Challenges

Linguistic bias cannot always be identified through individual words or expressions. The meaning of a sentence depends on its historical circumstances, authorial intention, documentary purpose, and surrounding discourse.

For example, a discriminatory expression may appear in a colonial administrator's original statement, an indigenous person's reported speech, or an anti-colonial critique quoting colonial terminology. Automated models may incorrectly classify all three occurrences in the same way.

Therefore, contextual interpretation requires historical expertise and careful examination of complete documents.

5.5 Algorithmic Bias in NLP Models

Modern NLP models may reproduce biases present in their original training datasets. If training materials contain Eurocentric perspectives or unequal cultural representations, automated systems may unintentionally reinforce similar assumptions.

Potential problems include:

- Overrepresentation of dominant languages.
- Underrepresentation of indigenous terminology.
- Unequal classification across ethnic and cultural groups.
- Reinforcement of stereotypical semantic associations.
- Inconsistent recognition of marginalized identities.

These limitations may undermine the central objective of decolonizing archival knowledge.

CONCLUSION

The study, “Decolonizing the Archive: Applying Natural Language Processing to Identify Linguistic Bias in Colonial Historical Records,” highlights the importance of integrating advanced computational technologies with critical

historical scholarship to identify and examine linguistic bias embedded in colonial archival documentation. Colonial historical records are valuable sources of information about political institutions, cultural practices, social relationships, and historical transformations. However, these documents frequently reflect the ideological assumptions, administrative priorities, racial classifications, and cultural hierarchies of colonial authorities. Consequently, critically examining their linguistic structures is essential for developing more inclusive and balanced interpretations of historical knowledge.

The proposed research demonstrates the potential of Natural Language Processing (NLP) techniques, including machine learning, deep learning, sentiment analysis, named entity recognition, topic modeling, semantic analysis, and transformer-based language models, to systematically investigate linguistic patterns within colonial historical records. The integration of these techniques can help identify discriminatory terminology, racial stereotypes, cultural superiority narratives, unequal representations, and recurring ideological associations. Furthermore, contextual language models such as BERT and RoBERTa offer opportunities to examine historical expressions beyond simple vocabulary matching by considering sentence structures and surrounding linguistic contexts.

An important contribution of the proposed framework is its ability to combine computational analysis with critical discourse analysis and historical contextualization. Dictionary-based approaches can identify potentially biased terminology, while machine learning models can classify linguistic patterns across extensive archival collections. Topic modeling and word embeddings can reveal recurring colonial narratives and semantic associations, whereas Explainable Artificial Intelligence techniques can improve the transparency of automated classification decisions. These approaches collectively provide a systematic foundation for investigating how language contributed to the construction and maintenance of colonial power relationships.

The study also emphasizes that linguistic bias cannot be understood exclusively through automated classification or sentiment scores. Historical language is strongly influenced by documentary purpose, authorial perspective, geographical context, cultural traditions, and changing linguistic meanings. Therefore, human expert validation remains essential to distinguish discriminatory expressions from historical quotations, critical commentary, and contextually neutral descriptions. Collaboration among historians, computational linguists, archivists, and indigenous scholars can improve the reliability and ethical responsibility of computational interpretations.

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