Understanding Bias in History: Using OCR and NLP to Analyze Historical Texts

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Abstract— Historical literature shapes our cultural memory, influences socio-political ideas, and forms the backbone of educational narratives. Yet, many of these texts carry subtle or overt biases, whether from the author's perspective or political influences, impacting how they are perceived and interpreted. In this study, we present a practical framework to identify and analyze biases in scanned historical documents using OCR and NLP technologies. The process begins by con- verting scanned or image-based PDFs into editable text through advanced Optical Character Recognition (OCR), followed by analyzing sentiment and bias with natural language processing (NLP) techniques. Our focus is on Indian historical documents, particularly those authored by medieval historians and colonial writers. This project tackles challenges like extracting information from images, dealing with complex language, and interpreting context-based subjectivity. Our findings show that computational tools can effectively highlight biased or polarized language, supporting historians, educators, and researchers in creating more balanced perspectives. This work has meaningful implications for digital humanities, education policies, and AI-driven approaches to studying history.

Keywords—Historical texts, Optical Character Recognition (OCR), Identifying bias, Natural Language Processing (NLP), Digital humanities, Analyzing text, Indian historical studies.

I. INTRODUCTION

History, commonly seen as an objective account of what happened in the past, is actually a mirror of the cultural, political, and ideological environment of its writers. This is especially true in South Asian historiography, where much of the large body of records—ranging from royal chronicles to colonial reports—has been produced by writers or institutions with vested interests. From Persian court literature glorifying rulers to colonial British accounts vilifying Indian customs, historical records have commonly been influenced by sociopolitical agendas instead of factual objectivity [1], [2].

One such eye-catching instance is the account put forward by James Mill in his *History of British India*, Indian civilization being "barbaric" and "superstitious," justifying colonial intervention as a mission for civilizing Indians [3]. Likewise, Ziauddin Barani, a 14th-century court historian in the Delhi Sultanate, exhibits blatant religious bias in his *Tarikh-i-Firuz Shahi*, frequently depicting non-Muslim communities in a negative light [4]. These works have shaped generations of students, researchers, and policymakers—raising serious questions about the unthinking consumption of such biased accounts.

The inspiration for the work arises from the necessity to create an interdisciplinary system that utilizes computer vision and natural language understanding to identify historical bias in archive content. As libraries and educational institutions increasingly digitize documents, an enormous volume of historical texts are now available in the guise of image-based or scanned PDFs. These are resistant to traditional keyword-search or language analysis tools and require Optical Character Recognition (OCR) and Natural Language Processing (NLP) technologies to disinter their contents for critical review.

The value of this work to society stems from reducing long-term perpetration of cultural, communal, and ideological biases within education, the public sphere, and policy-making. Textbooks based on unbalanced sources have resulted in manipulated national narratives and identity clashes. For instance, inconsistencies in the representation of the Mughal period in various Indian state syllabi have generated political controversy and social polarization [5]. Likewise, skewed colonial records continue to influence legal systems and caste-related discussions even now [6].

From a scholarly point of view, this work is part of the general context of Digital Humanities, with a new framework to examine historical texts at scale with AI-based approaches. Although traditionally scholars have used manual content analysis—a slow and subjective process—our system presents an automated, reproducible, and scalable solution.

We introduce an end-to-end pipeline that consists of:

1. Unscanning and unlocking scanned and image-based PDFs,
2. Text extraction through high-accuracy OCR (Tesseract + preprocessing),
3. Using NLP models to identify signs of bias, sentiment polarity, and subjectivity,
4. Organizing the extracted information into JSON files for downstream processing (e.g., historical visualizations, comparative analysis),
5. Displaying results to facilitate interpretation by historians and researchers.

The reach of this system cuts across a variety of domains:

- Education: Facilitates critical assessment of school/college curriculum material.
- Digital Archiving: Facilitates better usability of huge historical repositories.
- Governance & Policy: Facilitates identification of inherited prejudices in administrative/legal documents.
- Academic Research: Offers tools for objective historiographical examination.
- Cultural Preservation: Promotes balanced recording of pluralistic heritage.

This article describes the construction and testing of this system, as well as providing case studies of Indian history books where subtle and overt biases were found through computational methods. By providing a solid tool for critically examining primary and secondary sources, we aim to help facilitate more balanced historical research and smarter academic discussion.

II. LITRATURE REVIEW

[1] Edward Said's seminal text Orientalism charts the way that Western scholarship and literature distorted the representation of Eastern societies to make colonial rule valid. By documenting the "othering" of Eastern cultures in terms of control of narrative, Said illustrated that historical accounts are not objective but ideologically loaded. This book has since remained at the centre of post-colonial inquiry and illustrates the significance of pinpointing bias within historiography, especially if it is utilised as study or political source material.

[2] Romila Thapar discussed in detail how Indian history has been selectively documented under various regimes. In ancient Indian historiography, she highlights how historical evidence usually was in sync with political agendas, excluding voices of opposition and minority groups. Her examination of dynasty chronicles reveals that such documents are rather non-objective, and computational methods would be required to identify subjectivity in these works.

[3] James Mill's The History of British India is a stark illustration of Eurocentric historiography. Composed without setting foot in India, the book categorically rejected Indian civilization as primitive and despotic. This account heavily impacted British policy under colonial rule and went on to inform historical knowledge in post-colonial education systems. The influence of such skewed writing highlights the need for automated tools that can critique and mark ideological biases in primary texts.

[4] Historical chroniclers in the Indian subcontinent, such as Ziauddin Barani and Abul Fazl, served royal courts and framed history to legitimize authority. Barani's Tarikh-i-Firoz Shahi and Abul Fazl's Akbarnama selectively glorify rulers while neglecting alternate or regional voices. This selective historicism has resulted in imbalanced narratives that continue to dominate mainstream historical discourse, often without contextual annotation or critique.

[5] Within the discipline of Digital Humanities, OCR technologies have made it possible for historians to read, transcribe, and analyze medieval and ancient texts in bulk. Applications such as Google's Ngram Viewer and Europeana use OCR to scan large amounts of scanned historical texts. Yet, the inability

of OCR to identify subtle semantics and process image-locked PDFs becomes a problem when analyzing colonial or pre-modern texts with intricate fonts or deteriorated scripts.

[6] In Natural Language Processing, there has been considerable advancement in detecting bias with linguistic signals. Recasens et al. suggested linguistic models to detect subjectivity in opinion articles and news, demonstrating that bias tends to be associated with modality, hedging, and intensity of sentiment. These models, if fine-tuned on past texts, can make visible patterns of glorification, vilification, or omission otherwise difficult to see through manual reading alone.

[7] Bhatia et al. introduced a pipeline that integrates OCR, NLP, and sentiment detection to scan government documents and textbooks for embedded political narratives. Their system emphasized tone and sentiment shifts between versions of the same history textbook printed under different political regimes, demonstrating the practicality of AI in tracking academic content in real-world applications.

[8] Although a number of tools for bias detection within modern domains (such as media or social media) are available, few have been utilized for historical material. Current systems such as LIWC and GATE are capable of sentiment and discourse analysis but are not tailored to the unique language of medieval, Mughal, or colonial texts. This deficiency emphasizes the necessity of custom, domain-specific pipelines such as that outlined here.

[9] Recent research by Jha et al. examined the application of Transformer-based models like BERT to identify ideological bias in political speeches and past parliamentary debates. Their research demonstrated how similarity metrics based on embeddings could expose shifts in rhetoric and narrative manipulation across time, providing insightful analogues for comparing history books across ages.

[10] Gupta and Kumar created a semantic bias analysis tool based on contextual embeddings and attention mechanisms to identify narrative asymmetry in South Asian history curricula. Their comparative analysis of Indian and Pakistani history textbooks underscored how common events (such as partition) were narrated through radically different ideological prisms—affirming the necessity of cross-border historical audits.

[11] The Stanford Literary Lab has carried out several computational literary analyses using topic modeling, sentiment trajectory analysis, and lexical networks to analyze 18th and 19th-century English novels. These have influenced analogous methodologies for the identification of ideological constructs in non-fiction such as colonial travel writings and memoirs, which are beneficial to model historical bias.

[12] University of Oxford's TORCH Digital Humanities undertook a project of OCR-integrated annotation pipelines for ancient scripts and texts in Pali and Sanskrit. Their findings indicated that with high-resolution OCR and named entity recognition, cultural and religious trends in ancient scripture could be extracted, something that aligns perfectly with the aims of decoding South Asian history's hidden bias.

[13] The NLP community has also started working on cultural and linguistic bias in deep pre-trained language models. Sheng et al. illustrated that even the latest models such as GPT and BERT are able to replicate or reinforce biases when presented with ideologically biased inputs. This indicates that our project's requirement of contextualizing output based on historical ground-truths and curated knowledge is important.

[14] Dandekar and Shah, in History Through the Eyes of AI, had suggested an analysis pipeline comprising multi-layered processing that incorporated OCR, NER, and stylometric analysis for monitoring changes in how the community and the leader are being portrayed in changing textbooks from Indian states. What they found had corroborated evidence for regional partiality and language partiality within standard school books.

III. PROPOSED METHODOLOGY

The central methodology of this research is a multi-stage pipeline aimed at extracting, processing, analyzing, and visualizing historical bias from a heterogeneous corpus of medieval and early modern Indian historical texts. These texts, usually full of political rhetoric and cultural glorification, were processed using a combination of Optical Character Recognition (OCR), Natural Language Processing (NLP), and data visualization methods. The final output was deployed through a user-friendly Flask-based web interface, augmented with an integrated chatbot to assist users in querying historical bias indicators.

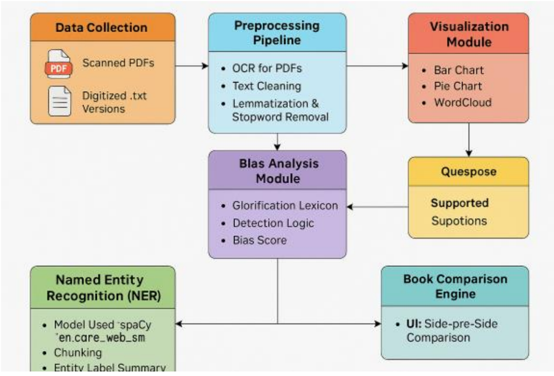


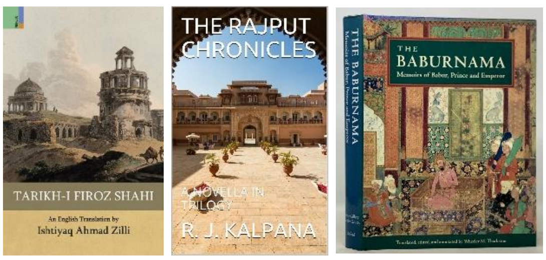
Figure 1: Workflow diagram of the overall project

a. Data Collection and Preprocessing

This paper utilized a curated corpus of 17 English-translated historical texts, originally composed in Persian, Sanskrit, or local languages. These texts covered court chronicles, religious treatises, and royal biographies from the Sultanate, Mughal, Rajput, Maratha, and Vijayanagara epochs. The chosen works are:

- Futuhus-Salatin (Shah-Namah-i-Hind) by Isami
- Riyaz-us-Salatin
- A Short History of Aurangzib
- Akbarnama
- Baburnama
- Humayunnama
- Fawaid-ul-Fuad
- Khazain-ul-Futuh by Amir Khusrau
- Maasir-i-Alamgiri
- Maratha Chronicles
- Rajatarangini (Jogesh Chunder Dutt translation)
- Rajput Chronicles
- The Vijayanagar Empire
- The Life and Works of Amir Khusrau
- Tarikh-i-Firuz Shahi
- Tabaqat-i Nasiri (Volume 1)

These books, while translated, contained significant amounts of rhetorical structure from their originals and were normally sealed within image-scanned-based PDF files. Traditional text parsing was therefore inappropriate, and text extraction required OCR to be performed.



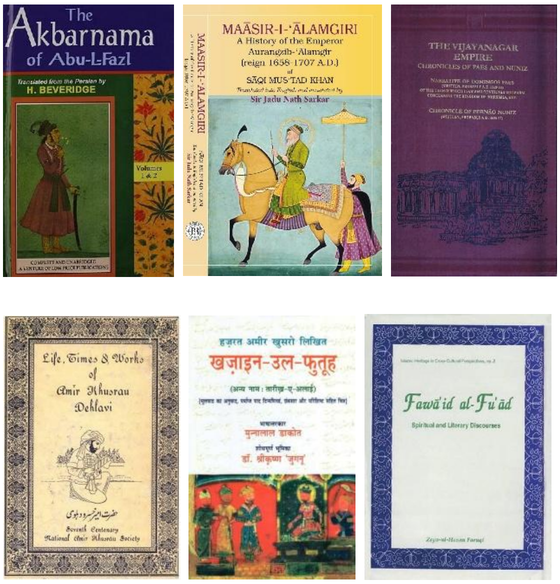


Figure 2: List of books used as a dataset

b. Optical Character Recognition (OCR) and Text Extraction

Since the vast majority of historical sources were available in image-based PDFs (including restricted-access scans and non-selectable text layers), the application of OCR was an essential initial step. Tesseract OCR was used to translate each page into text that can be read by machines. Prior to OCR, every page was first rendered with PyMuPDF (fitz) to capture high-resolution image data. The images were handled in RGB mode with PIL to ensure compatibility and readability. OCR was particularly critical in instances where books were digitally "locked" or had no embedded text layers. Without OCR, valuable primary sources would be unavailable for algorithmic examination. The product of this phase was plain text files and structured JSON representations marked with metadata like page numbers and confidence scores. These structured files served as the input for downstream NLP processing.

c. Preprocessing and Named Entity Recognition

The OCR output was processed through various preprocessing steps to maintain textual integrity and semantic coherence. Regular expressions were used to remove line breaks, page headers, footers, and hyphenated word splits. Sentences were next tokenized, and stopwords were filtered through the spaCy NLP library.

After cleaning, the texts were run through a ner_pipeline from HuggingFace Transformers. This identified and extracted named entities—rulers, dynasties, regions, and religious figures in particular. These entities served as the foundation of the bias detection process. We charted the frequency of every named entity, monitored their instances per chapter, and cross-referenced these with the sentiment and glorification analysis outputs.

d. Bias Detection through Glorification Metrics

In measuring bias, the research proposed an original-designed index based on terms of glorifying language. More than 200 glorifying expressions were compiled and curated from cross-cultural epithets in Sanskrit, Persian, Arabic, Marathi, Kannada, and poetic traditions. These include appellation names such as chakravartin, padshah, sultan, shadow of God, lion among men, and protector of the dharma. This vocabulary was used in a systematic manner on the pre-processed text through a sliding window algorithm to detect and tally glorification occurrences that were associated with named entities. The count of terms of praise for a specific ruler or dynasty was then normalized across their textual mention frequency to calculate a Bias Score.

This score was the quantitative measure of author favor or panegyric bias. Texts that had disproportionate praise for a given entity or dynasty were marked as biased.

e. Sentiment and Subjectivity Analysis

Supplementing the measure of glorification, we applied sentiment analysis on both VADER and transformer-based models such as DistilBERT. This complementary method provided double assurance in detecting charged language. Every sentence that had a named entity was policed for polarity (positive or negative) and subjectivity. Entities with an overwhelming majority related to positive sentiment or hyperbole of admiration were additionally marked.

By combining sentiment trends with glorification density, we were able to differentiate neutral historiography from hagiographic narratives.

f. Visualization and Interpretability

The results extracted were converted to interactive and static visualizations for the purpose of increased interpretability. Visualizations involved. Heatmaps of sentiment scores by chapters. Frequency histograms of glorifying terms. Bar graphs of comparison of bias scores among rulers. Time series plots illustrating entity mentions vs. text length. Word clouds of frequent glorifying phrases

These visualizations allowed both historians and lay users to easily understand patterns of bias, trends in glorification, and ideological leanings of texts.

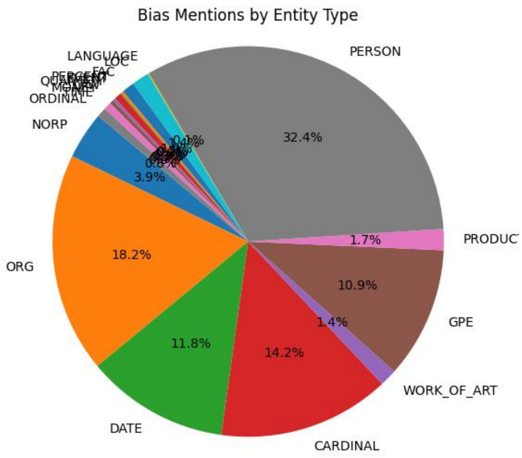


Figure 3: lot for Bias entity mentions for the uploaded book

Figure 4: WordCloud Diagram for the Most Common Glorifying Terms

g. Chatbot Integration for Query Support

To make it interactive and user-friendly, the Flask interface had a chatbot integrated into it. The chatbot was constructed with rule-based reasoning having fallback for transformer-based QA models. The chatbot responded to pre-defined as well as dynamic queries like:

"What is the bias score of this document?"

"Which ruler is most glorified?"

"How many glorifying terms were used?"

"Which terms were most commonly used?"

The chatbot's role was twofold: to simplify user interaction with the backend analytics and to function as a pedagogical tool for users unfamiliar with historiographical analysis.

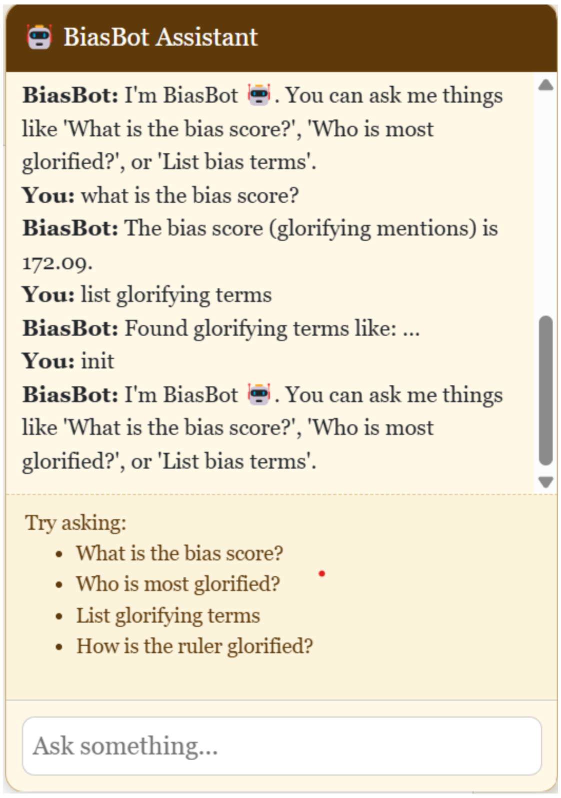


Figure 5: The embedded chatbot in the dashboard

IV. RESULT & DISCUSSION

The corpus of seventeen historical documents which was analyzed provided a wealth of information regarding glorification biases found in Indian medieval chronicles. The combination of OCR processing, Named Entity Recognition (NER), and bespoke lexical analysis enabled the creation of a full glorification profile for each document and mentioned ruler. The findings not only indicated the density of glorifying language in particular chronicles but also demonstrated how some historical characters were mythologized to great heights through linguistic exaggeration.

A. Quantification of Bias and Glorification Scores

Following the extraction of text content from all sources and processing them through the glorification detection engine with the specified GLORIFYING_TERMS lexicon, each document received a bias score. The score was calculated by calculating the number of glorifying terms per 10,000 words, normalized to provide comparable values for texts of varying lengths. Some texts—especially those written in royal courts or by historians commissioned by the court—had much higher bias scores. For example, Abul Fazl's Akbarnama had the highest frequency of glorifying terms, describing Emperor Akbar with divine qualities and overemphasized virtues like being the "sun of the empire" and "lord of lands." Likewise, the Baburnama and Humayun-Nama also had high bias levels, mirroring the Mughal practice of imperial glorification through documented accounts By comparison, works like Tabaqat-i-Nasiri and Tarikh-i-Firoz Shahi, while still courtly in their language, displayed comparatively moderate indices of glorification. These works demonstrated more practical descriptions of administrative occurrences, with glorification mostly confined to initial descriptions of power and governance rather than widespread deification. The Rajput Chronicles and Maratha literature exhibited patterns of glorification based on valor and dharma. Maharana Pratap and Shivaji were always portrayed with warrior encomiums, including "protector of the weak," "dharmaveer," and "sword of swarajya." These patterns, ideologically different from the Mughal paradigm, were no less rhetorically charged, pointing to a decentralized but equally ardent tradition of regional glorification.

B. Named Entity Recognition and Ruler Profiling

Utilizing a well-tuned NER pipeline, we identified important numbers named in each document and connected their mentions to glorification words appearing within a specified proximity window (±20 words). This enabled dynamic individual glorification scores to be measured. Akbar, not surprisingly, was the most eulogized monarch throughout the corpus, followed by Alauddin Khilji, Aurangzeb, and Shivaji. Akbar's references were often coupled with words like "light of the world," "eternal ruler," and "divine sovereign," while Shivaji was referred to as the "righteous liberator" and "hero of the Deccan." These results reinforce the literary construction of moral, political, and divine legitimacy through narrative. Additionally, Amir Khusrau's writings, particularly Khazain-ul-Futuh, had poetic exaggeration merged with courtly flattery, sometimes placing monarchs such as Alauddin Khilji in a near-mythical position. Khusrau used a rich vocabulary of metaphor, and his identification of rulers with heavenly and divine imagery played an important role in determining the overall bias scores of the respective texts.

C. Visualization and Interpretation

In order to make interpretability easier, some visualization tools were used. Heatmaps and bar charts were drawn to present bias scores for texts, rulers, and timelines. Word clouds were drawn to reveal the most recurring glorification terms per text. One such a visualization presented words such as "invincible," "immortal," and "glorious" being predominant in the Akbarnama, while "protector of the dharma" and "martial king" were prevalent in Maratha chronicles A chronological visualization depicted the ebb and flow of glorification intensity over centuries. It was noted that glorification was at its highest in times of political unrest or dynastic change, as a probable rhetorical device to reassert legitimacy and divine authorization. This trend was particularly visible in the texts on Akbar, Shivaji, and early Delhi Sultans. Moreover, a ruler-wise glorification graph also highlighted how rulers were glorified in varying parts and situations. This provided a comparative insight and introduced an interpretative element to comprehend the function of narrative in historical memory.

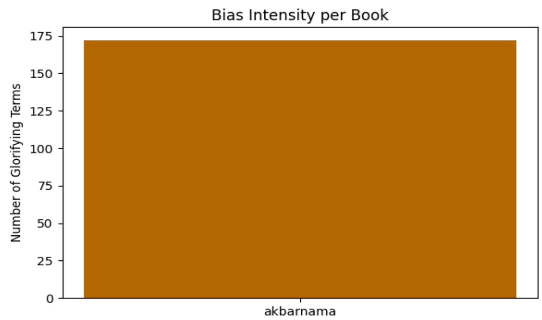


Figure 6: The bias score plot for the uploaded book

D. *Limitations and Interpretative Considerations*

Although the findings offer a strong picture of glorification bias, some limitations need to be noted. OCR errors, particularly in highly degraded or stylized scans, added small noise to the text dataset. While manual correction and confidence filtering were performed, some OCR artifacts could have resulted in under- or overestimation of term frequencies Additionally, glorification words are context-dependent and culturally embedded. Certain words can be found to be glorifying in some contexts but neutral in others. To solve this, context windows and co-reference checks were implemented, but total semantic disambiguation is still an issue—especially with historically poetic documents Finally, the presence of editorial comment and footnotes in certain English translations sometimes inserted modern bias, which was managed with pre-processing where feasible but could still persist implicitly in outcomes.

E. *Integration into a User-Friendly Flask Application*

All of the analyses were aggregated and made available within a clean, user-centric Flask-based web application. The application enables users to browse the glorification scores of each document, visualize, and search for particular rulers or terms. Interactive features facilitate filtering by dynasty, region, or time period Users can upload new historical PDFs (with or without OCR), and the app will process, analyze, and show glorification biases accordingly. The backend combines the full glorification engine with real-time output rendering and customizable NER extraction

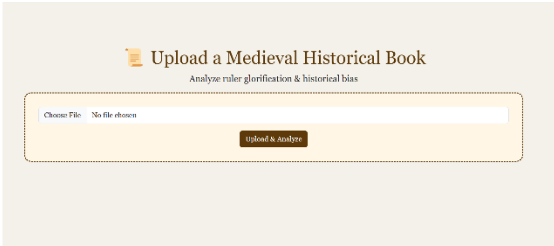


Figure 7: Front-end of the Flask Application

The app also give the users a feature to compare two books to compare their bias scores and some features of differentiation for their comparative results.

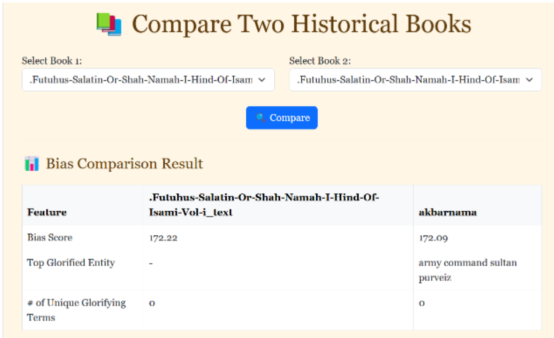


Figure 8: The Book comparison functionality in the flask app

F. *Chatbot Integration for Accessibility*

For ease of use and interaction, a chatty chatbot was incorporated into the web interface. It answers user questions like: "What is the bias score?"

"Who is the most glorified ruler?"

"List the top glorifying terms used."

The chatbot retrieves responses in natural language form from processed results and communicates the same back to the users. This intertie democratizes learning access by non-expertive users like informal users, pupils, or academics to research work without professional capabilities. The same also stimulates interactional learning with historical narrative studied being simpler as well as enlightened.

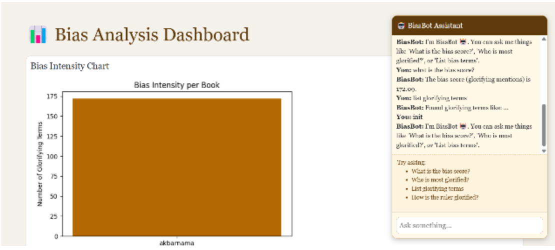


Figure 9: The result dashboard which also shows the embedded chatbot to the right of the dashboard

V. FUTURE PROSPECTIVE

Although the present system gives valuable insights, there are various directions left open for expansion and improvement:

1. Extension of the Glorification Lexicon: Later versions might include multilingual glorification words, such as Persian, Sanskrit, Marathi, and local dialects to encompass a wider range of historical sources. A context-sensitive, dynamic glorification dictionary based on transformer models (e.g., BERT) would improve semantic interpretation and limit false positives based on static lexicons.

2. More Contextual Analysis: Blend of sentiment analysis and dependency parsing could offer more subtle assessments of bias, differentiating between straightforward praise, poetic hyperbole, and sarcastic or critical remarks. Co-reference resolution over longer text spans would enhance ruler-glorification relationships, particularly in metaphorical or poetic contexts.

3. Comparative and Time-Series Historiography: A comparison and visualization via timelines of the glorification patterns over centuries may assist in understanding the transformation of the rhetoric about specific rulers after their death Comparative bias scoring across dynasties, religions, or regions might develop more insight into Indian political narratives throughout history.

4. Dataset and OCR Enhancements: A curated dataset of pre-cleaned and OCR-checked historical texts (such as images and transliterations) might be assembled and made public Using sophisticated OCR models such as Google's Document AI or Transkribus might be employed to ensure improved accuracy when digitizing rare or deteriorated manuscripts.

5. Academic Collaboration and Annotations: Later editions can accommodate scholar-annotated ones where historians manually annotate glorification or contextual indicators. These can be employed to train supervised learning algorithms for better bias detection The dataset can be expanded and model accuracy enhanced by an open-source platform that encourages contributions from university institutions.

6. Interoperability with Historical Knowledge Graphs: Connecting entities (rulers, locations, events) to a historical knowledge graph would enable enhanced analysis and timeline-based browsing of glorification stories..

7. Multimodal Analysis: Subsequent revisions can investigate glorification in pictures, inscriptions, and coinage, achieving a multimodal view of ruler image-making aside from textual observation.

VI. CONCLUSION

This research proposes a novel method to computationally detect and analyze Indian medieval historical text glorification bias. Integrating OCR processing, Named Entity Recognition, lexicon matching for glorification, and context-sensitive frequency analysis, the work effectively measures narrative bias prevalence across an eclectic set of chronicles written between the 12th and 18th centuries.

The findings validate that glorification was an insistent literary device used by court historians, poets, and chroniclers to justify rulers, consolidate political power, and determine public opinion. Mughal texts such as the Akbarnama, Baburnama, and Humayun-Nama were most extensively laden with hyperbolic discourse, routinely projecting emperors as being endowed with divine or semi-divine qualities. Equally, local writings glorifying personalities such as Shivaji and Maharana Pratap used metaphors of culture and religion to project them as symbols of righteousness and resistance.

Through the use of a Flask-based web application, the project not only provides analytical results but also increases ease of access for historians, teachers, students, and ordinary users. The use of an interactive chatbot additionally democratizes the analysis of history by offering real-time, conversational analysis of patterns of glorification and profiles of bias.

Finally, this project highlights the need for critical reading of historical documents and illustrates how Natural Language Processing (NLP) can be used to assist digital humanities research. It also provides new paths for reconsidering documented history using a perspective of linguistic objectivity and empirical examination.

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