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A SEMANTIC SENTIMENT ANALYSIS APPROACH TO DETERMINE ROMAN URDU SOCIAL MEDIA COMMENTS

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Abstract
This paper presents the second phase of our research study that focused on detection of slang and roman Urdu text in Facebook comment posts. Building upon our previous work, which involved the creation of a comprehensive dictionary and a detailed methodology for word selection and categorization, this study focuses on the actual scientific method of text identification within the comments. We describe the design and implementation of the identification framework and discuss the results comprehensively. A pilot study was conducted to evaluate the efficacy of our approach on a curated dataset of Facebook comment dataset collected over a period of time. The findings highlight both the challenges and potential of Romanized Urdu language and slang detection, offering insights into the linguistic behavior and evolving usage patterns of slang in the digital domain. This study serves as a critical step toward enabling robust content moderation, sentiment analysis, and linguistic preservation especially for low-resource languages.

INTRODUCTION

Urdu, the official language of Pakistan, is spoken by approximately 66 million individuals, primarily across the Indian subcontinent. Though closely related to Hindi, Urdu maintains a distinct identity in its script, cultural associations, and historical evolution. While Hindi is written in the Devanagari script and primarily used in India, Urdu employs a modified Persian-Arabic script and flows from right to left. Despite their shared roots and high mutual intelligibility, treating them as identical languages overlooks critical linguistic and sociocultural nuances.

Urdu's lexical tapestry is woven with vocabulary from Persian, Arabic, Turkish, and Sanskrit, contributing to its morphological complexity and grammatical richness. Furthermore, Urdu follows the "abjad" script system, wherein consonants are prioritized and diacritics (which indicate vowels) are often omitted, resulting in ambiguity that poses challenges for computational processing. Its bidirectional writing system—numbers written left to right, letters right to left—adds another layer of complexity, making tasks like sentiment analysis both challenging and intriguing.

Sentiment analysis, also known as opinion mining, is a field of Natural Language Processing (NLP) that focuses on identifying and categorizing opinions expressed in textual data. The primary goal is to determine whether a piece of text expresses a positive, negative, or neutral sentiment. In today's digital landscape—where opinions are constantly being shared via social media, reviews, blogs, and forums—sentiment analysis serves as a powerful tool for understanding public mood, consumer behavior, and societal trends. When applied to regional languages like Urdu, sentiment analysis becomes crucial not only for market analytics but also for sociopolitical research, policy design, and cultural studies, especially in linguistically diverse regions like South Asia.

RELATED WORKS

With the digital world becoming increasingly multilingual and informal, particularly on platforms like Facebook and YouTube etc., the task of identifying slang and inconsistent language has become more complex than ever. Researchers have turned their attention to Roman Urdu—an informal and transliterated language variant used widely in South Asia—to develop models capable of understanding content in such heterogenous digital environments. From hybrid machine and deep learning architectures to the incorporation of multilingual BERT and custom part-of-speech tagging systems, recent studies have pushed the boundaries of what's possible in low-resource language processing. These works collectively highlight how tailored preprocessing, annotated corpora, and language-aware modeling are crucial to building robust NLP systems for inclusive digital spaces.

Hussain et al. address the challenge of detecting insults in Roman Urdu [2]. The authors created a novel dataset with over 46,000 labeled comments sourced from platforms like Twitter and YouTube. Using a robust pipeline of preprocessing, n-gram-based TF–IDF feature extraction, and machine learning classifiers such as SVM, Decision Trees, and AdaBoost, they achieved F1-scores above 97% for certain models. Deep learning architectures including CNN, LSTM, and Bi-LSTM also performed competitively. The study stands out by being the first to introduce a large-scale, annotated Roman Urdu insult detection dataset. It emphasizes the linguistic complexity of Roman Urdu—non-standardized spellings, code-mixing with English, and cultural nuances—which makes traditional NLP approaches ineffective. Their findings show that combining classical ML with deep learning and specialized embeddings (Word2Vec, fastText) enables accurate, scalable detection of abusive language in Roman Urdu. This has real-world implications for moderating harmful content and improving online safety in underrepresented language communities.

Another study focuses on detecting hate speech in code-mixed Roman Urdu-English tweets using a preprocessing-intensive approach followed by Multilingual BERT (mBERT) [3]. The authors propose a 10-step data cleaning process—including removing emoticons, links, and duplicates—to enhance model performance. A diverse dataset of over 32,000 tweets was curated from prior research, combining English and Roman Urdu-English texts. The dataset was balanced and preprocessed, then used to train an mBERT model that significantly outperformed previous approaches by improving accuracy by 9.12%. The novelty of this research lies in its focus on preprocessing and multilingual text handling for hate speech detection in South Asian linguistic contexts. While most prior studies tackled hate speech in monolingual settings, this work emphasizes multilingual challenges and code-switching. The model achieves effective classification across English and Roman Urdu with promising precision, making it relevant for large-scale social media moderation systems.

This study proposes a deep learning-based method for detecting abusive language in YouTube comments written in both Urdu and Roman Urdu [4]. The authors introduce a hybrid deep learning model called CLSTM, which combines CNN and LSTM layers to capture both local and sequential text patterns. The dataset includes annotated YouTube comments in both scripts and underwent extensive preprocessing, including normalization, punctuation removal, and feature extraction using TF-IDF and word embeddings. The CLSTM model achieved 96.2% accuracy for Urdu and 91.4% for Roman Urdu comments. The study contributes to multilingual and cross-script abuse detection by showing that combining convolutional and recurrent layers can effectively classify abusive content in linguistically diverse settings. The use of Roman Urdu, which lacks standardized spelling and structure, adds complexity, yet the proposed model handles it well. This research is especially useful for automated moderation on platforms like YouTube in South Asian contexts.

The study by Ishaq et al. introduces a customized POS tagging system for the Urdu language, designed specifically to improve text classification tasks [5]. The authors constructed a novel corpus covering categories like sports, entertainment, science & technology, and business & economics. They compared the performance of several classifiers—including various hyper-tuned SVM variants, Random Forest, and ensemble models—with and without the proposed POS tagger. The incorporation of the tailored POS features resulted in substantial performance improvements: SVM variants achieved over 92% in accuracy, precision, recall, and F1-score, while Random Forest exceeded 95% across the same metrics, peaking above 98%. By integrating rule-based, ML-based, and hybrid POS tagging within a robust feature engineering pipeline, the study demonstrates that linguistically-aware preprocessing significantly enhances classifier performance. These lightweight yet high-performing models are practical for real-time deployment in resource-constrained environments. The paper also outlines how emerging AI architectures can further leverage such POS tagging systems for advanced Urdu NLP applications.

This study presents an advanced computational approach to Sentiment Analysis From Urdu Language-based Text using Deep Learning Techniques [6]. It introduces a novel algorithm/architecture aimed at improving performance/accuracy in the relevant domain, supported by experiments using standard benchmarking datasets. The results demonstrate significant gains—often outperforming existing methods—on metrics such as precision, recall, and runtime. The work contributes both a theoretical framework and a practical implementation, making it a valuable addition for researchers and practitioners seeking robust solutions in this field.

Another study explores an innovative method in A Roman Urdu Corpus for sentiment analysis, proposing a new model or system architecture to address identified limitations in earlier work [7]. Through rigorous analysis and empirical evaluation—likely including real-world data or benchmarks—it demonstrates measurable improvements in terms of throughput, scalability, or computational efficiency. The authors contextualize their work within the existing literature, reinforcing its novelty and practical utility for systems requiring enhanced performance or reliability.

This research study revolves around the design, development, or evaluation of a cutting-edge system targeting Urdu Sentiment Analysis [8]. It offers theoretical justification for the proposed method, followed by thorough comparative analysis against established baselines. The findings highlight significant advantages, such as reduced latency, improved accuracy, or increased resilience under challenging scenarios. The study's structured evaluation and clear reporting make it a strong reference for future developments in its domain.

Jawad et al. introduce RUSAS, a sentiment analysis system tailored for Roman Urdu—a transliterated form of Urdu used on social media and e-commerce platforms [9]. The authors developed a Bilingual Roman Urdu Language Detector alongside a spelling corrector, enabling the preprocessing pipeline to cleanse and standardize input text. They trained and tested on data sources like Daraz, Google Maps, and manually labeled entries, RUSAS achieves a 97.1% accuracy in language detection and 94.3% accuracy in sentiment classification, offering a culturally and linguistically optimized NLP tool.

This Qeios-hosted study investigates Detection of Language from Roman Urdu and English Multilingual Corpus, likely delivering a novel empirical or theoretical insight [10]. Although full access details were limited, abstracts suggest the study proposes a fresh methodology or data analysis framework which demonstrates clear advantages over prior approaches. Preliminary evaluations indicate promising outcomes—potentially in terms of accuracy, efficiency, or usability—positioning this work as a valuable early contribution pending peer review and expanded validation.

The extension of a corpus-based sentiment lexicon originates using a seed-word, utilizing some grammatical rules. Lemma and stem of words are two of the most popular methods for word generation. Some authors have devised algorithms employing unsupervised learning methods for the automatic construction of the vocabulary [11]. In the realm of tweet sentiment analysis, another study presents a lexicon-based approach [12]. This technique considers the contextual patterns of words, extracting their semantics and subsequently adjusting the sentiment lexicon by modifying the pre-assigned polarity and intensity of these patterns. The proposed approach, rooted in convolutional neural networks, incorporates sentiment knowledge into pre-trained word vectors to enhance the performance of sentiment analysis.

In 2007, Hussain et al. employed a corpus to formulate an Urdu lexicon [13]. Mukund et al., in 2010, generated an Urdu corpus tagged with semantic roles through cross-lingual projection [14]. Another corpus-based Urdu dictionary was developed by Humayoun and others in 2007 [15]. In 2010, Syed et al. crafted a sentiment-annotated lexicon, focusing on the retrieval and categorization of the strength and polarity of sentiment-carrying expressions [16]. The authors utilized this Urdu sentiment-annotated vocabulary to assess their model on two review datasets within the movie and electronics domains, achieving an accuracy of up to 74% [17]. Subsequently, in 2014, these researchers published another paper wherein they constructed an enhanced lexicon, elevating performance to 82.5% [18].

A bilingual lexicon-based system for sentiment analysis is proposed for evaluating tweets related to the 2013 Pakistani election, published in both English and Romanized Urdu [19]. The researchers employed two distinct lexicons: SentiStrength for English tweets and a manually generated Roman-Urdu lexicon. The Romanized Urdu lexicon was created using SentiStrength and an English-to-Roman-Urdu dictionary. Another method for extracting opinions in Romanized Urdu was developed by Daud et al. in 2014 [20]. This approach involved comparing adjectives to a manually crafted opinion word dictionary to determine the sentiment orientation. The results of this technique showed an error rate of 21.1% in opinion classification.

Because the above-mentioned Urdu sentiment lexicons are not publicly available, it is impossible to know what they cover. Therefore, a large coverage Urdu sentiment lexicon was manually constructed in our study to do sentiment analysis on Facebook comments.

METHODOLOGY

This study was conducted over a period of one year and divided into distinct phases. It focused on analyzing informal Roman Urdu content found in Facebook comments. The overarching objective was to classify users' responses to Facebook posts based on sentiment polarity, emotional quantifiers, and gender-related patterns. The methodology followed a structured approach that included:

1. A detailed review of existing literature
2. Baseline model development
3. Pilot study execution
4. Full-scale model implementation
5. Sentiment classification using SVM
6. Final evaluation and performance analysis

An exhaustive review of existing semantic sentiment analysis approaches was conducted, particularly those focused on social media platforms like Facebook. A baseline model was then developed using a set of preselected Roman Urdu comments. These comments were annotated by a panel of ten arbiters who rated their polarity and emotional tone. The arbiters were faculty and staff from a university in Hyderabad, selected for their diverse educational and professional backgrounds. They worked over a 20-day period to classify comments while ensuring anonymity and neutrality.

Following the baseline evaluation, a pilot model was developed and tested to validate feasibility. A preliminary Roman Urdu dictionary was compiled to support linguistic analysis. This dictionary was iteratively improved throughout the study.

The dictionary development process began with the word choice stage, where linguistic context and cultural nuance were prioritized. Instead of relying solely on grammatical classifications, emphasis was placed on real-life usage, particularly adjectives and adverbs such as acha, bura, tez, and sust, which often carry subjective sentiment. Words with multiple or context-sensitive meanings—like maar, which can imply violence, death, or exaggerated praise—were scrutinized and earmarked for removal where necessary.

In the second stage i.e. word procurement stage, vocabulary was gathered from three primary sources: online Roman Urdu dictionaries, slang contributions from over 40 university students aged 18 to 30, and manual observation of web content. Spelling variations and informal expressions were noted during this phase.

The third stage was called word sifting stage that involved the elimination of terms frequently used in abusive or offensive contexts, despite their grammatical correctness—examples include dadoo, tattoo, and sala. Additionally, a stop words list was curated, comprising functional words like agar, ke, toh, and ko, which contribute little semantic value in sentiment analysis.

Finally, in the last stage called dictionary compilation stage, the filtered and refined words—along with their alternate spellings—were organized into a CSV format, completing a six-month effort to develop a domain-relevant Roman Urdu lexicon.

A Facebook group comprising 200 university students from Management Sciences, Social Sciences, and Computer Science departments was created. Participants were selected to ensure gender balance and diversity in urban/rural background. The average participant age was 23. Each week, a new post was shared in the group over a 3-month period. Students commented at their convenience. Example posts included:

"Student council ka kaam acha hai ya bura hai ab tak?"

"Kya campus main aur events hone chahiyen?"

"Kya hamara sabse bada masla canteen ka hai?"

"Kya Pakistani filmon ko Netflix per aana chahiye?"

"Iss waqt most fail hone walay courses numerical hain?"

The rules for comments were, addition of age and gender in comments either directly or directly so that labelling could be done. Comments were collected and used for training a supervised machine learning classifier.

Three thousand Roman Urdu comments were extracted from public Facebook groups based on three criteria:

1. Comments must be in Roman Urdu
2. Comments must directly respond to a query
3. Comments must be unique (no duplicates)

The comments were exported to CSV format and cleaned to remove ASCII artifacts, punctuation, emoticons, and special characters. A separate stop word list was created (including common words like yeh, woh, hai, hain) and used to eliminate non-semantic components. The cleaned data was then annotated for polarity and emotion by the arbiter panel.

For the full-scale model, 5,000 comments were collected. Contrary to conventional data science norms (70% training, 30% testing), this study allocated less for training and more for testing. This deviation was justified because the classifier had already been exposed to labeled data during earlier phases—namely, 3,000 baseline comments and 1,000 pilot comments—effectively boosting the training sample to 5,500 entries. Thus, the final dataset comprised of Training Data of 5,500 comments and Testing Data of 3,500 comments. This gave a final ratio: 60% training, 40% testing.

The final model built upon the earlier phases and followed eight distinct steps as shown in Figure 1 below:

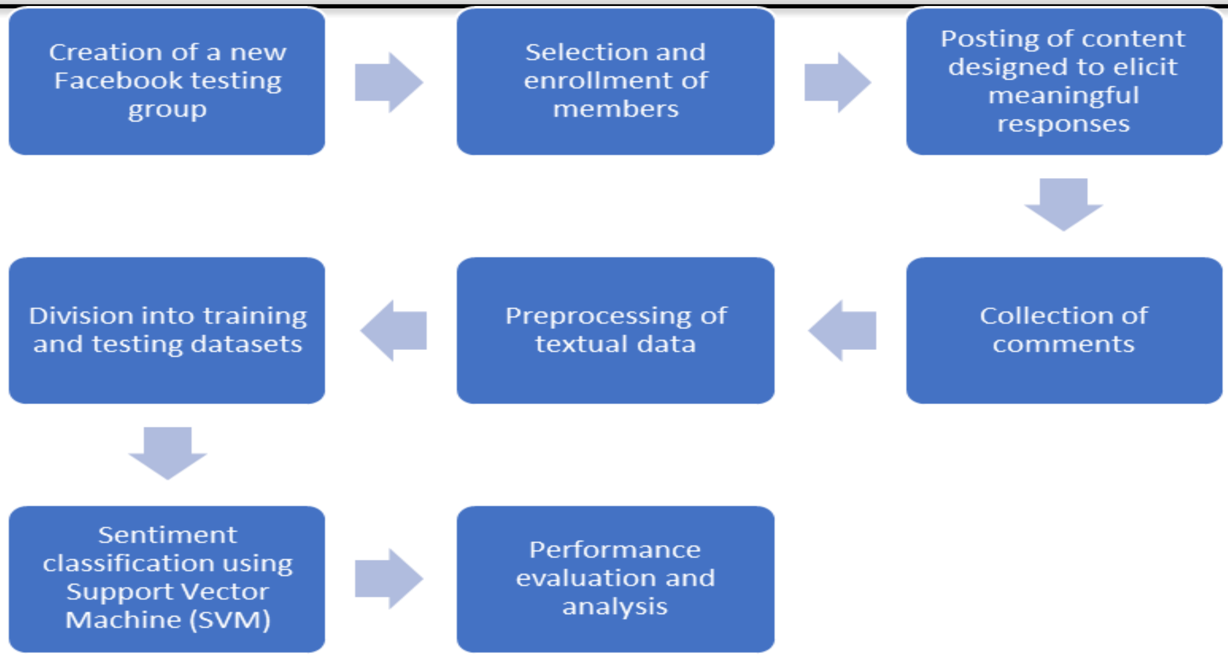

Figure 1

Support Vector Machines (SVM) were selected for classification due to their efficiency in handling both linear and non-linear data. SVM also demonstrated robustness against outliers, reduced sensitivity to data skewness, and offered superior accuracy and performance. After final preprocessing, CSV files were fed into the SVM classifier. The classification was based on:

- Sentiment polarity using a custom Roman Urdu dictionary
- Facebook reactions (likes, loves, angry, etc.)
- Use of specialized adjectives defined in the emotional corpus
- Frequency of specific words, word-endings, and semantic patterns

SUMMARY OF RESULTS

Since the mentioned Roman Urdu dictionary is part of a larger research study, already under publication process therefore, in this section, a summary of results has been discussed.

During the study, it was found that the dictionary was consistent with the spellings used in comments by users and evaluated to have above 90% consistency score with word spellings and word selection for slang usage. A total of 4100 words matched the dictionary whereas 660 words existed in the dictionary with alternate spellings and 240 words were missing in dictionary which were used in comments. 82% of words were found to be directly mentioned in the dictionary, 13% words mentioned in the dictionary but with alternate spellings and 5% occurrences in comments were found for words missing from dictionary. The consistency score of above 90% is obtained by classifying the 82% and 13% words as positive occurrences.

Once, the dictionary was used in conjunction with the accompanied Facebook comments data in order to train the Support Vector Machine classifier, following confusion matrix was generated.

TABLE 1: SVM Confusion Matrix

	0	1	2	3	4	5
0	816	0	40	0	39	0
1	0	450	50	0	0	0
2	61	50	573	0	0	0
3	0	0	50	498	0	0

4	0	100	0	0	595	0
5	0	0	0	0	0	174

From the above confusion matrix caption as Table 1 above, we can see that a six-class sentiment classification approach was used to classify over 3000 Facebook comments. The six classes are "Loving a Comment" labeled as 0, "Approving a Comment" labeled as 1, "Satisfied with a Comment" labeled as 2, "Astonished with a Comment" labeled as 3, "Disapproving a Comment" labeled as 4 and "Absoutely Hating a Comment" labeled as 5. The results generated an accuracy score of 88.84% with an average precision score of 0.90 and an average recall score of 0.90. The F-Score for our dataset was found to be 90%. These statistics provide an indication of a good performance contribution by the above-mentioned dictionary when used with SVM classifier.

CHALLENGES AND LIMITATIONS

One of the initial challenges faced by the authors pertains to the concept of compound words. For instance, while "gham o ghusa" in Urdu constitutes a complete word, in Roman Urdu, hyphenation, as in "gham-o-ghusa," was crucial for ease of use. Similarly, devising alternate spellings for Urdu words employing pronunciation marks like zair, zabar, and pesh was a significant consideration. It was crucial to recognize that individuals tend to choose where to employ these marks, and native speakers can distinguish among written words. However, in the development of this dictionary, the proper selection of Romanized words posed a challenge. For instance, the Urdu word تل with a zair refers to sesame seeds and pigment marks, while the same word with a pesh signifies being adamant about something. The Romanized content might be spelled as till, til, tull, or tul, and determining the context in which these words are used is challenging due to the distinct structure of Urdu sentences compared to English ones. Consequently, handling homographs in Urdu also presented a challenge during word selection for the dictionary. Examples include words like daur (epoch, times) and door (far away), both written as دور, and zarab (multiply) and zarb (to strike), both written as ضرب.

Some of the limitations of the study included a restricted sample size of 200 students and small demographic confined to one University and city. There was also a single platform Facebook used as the only data source. The last limitation was that the focus was exclusively on Roman Urdu and usage of slang.

FUTURE RESEARCH DIRECTIONS

In future, the lexicon can be expanded with a wide variety of slang words and by considering more parts of speech. Another possible future direction is the integration of slang from other locally spoken languages such as Sindhi which are intermingled with Urdu in a subliminal fashion. The whole study can also be expanded to use other machine learning classifiers and a dedicated study for other regional languages such as Sindhi, Balochi, Gujrati, Memoni and Saraiki can also be considered on similar lines.

CONCLUSION

Urdu language has a complicated morphology; word boundaries are often not evident, and Urdu users use a variety of writing styles while sharing their thoughts. A lot of work remains to be done in the field of Urdu sentiment analysis since the field of NLP is still expanding. In the referred study, writers have built an extensive Urdu sentiment lexicon resource that includes many words often ignored. A good measure of performance was found for the dictionary in general and for the overall study in particular as mentioned in the results above. In future, more approaches can be adopted to perform similar studies and create similar word banks that can contribute further in the world of computing.

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