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SPAM DETECTION IN ROMAN URDU REVIEWS USING SPAMMER BEHAVIOR FEATURES

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ABSTRACT
Reviews have emerged recently as the most important basis on which it is decided whether offered products and services are good or bad. Therefore, customer reviews concern sellers because they may directly affect the growth of their respective businesses. Unfortunately, there is a growing trend towards writing spam reviews to promote certain targeted products. This practice goes well in review spamming. Though the SRD problem has drawn much attention, all the existing studies on SRD work on either an English or Chinese dataset or on any other language. Urdu stands at 10th position in the rankings of most spoken languages in the world. There is a dire need for such a system/model which detects Spam Reviews, specifically typed in Roman Urdu. Therefore, the aim of this research will be spam detection in Roman Urdu review classifications based on various models by using linguistic features and behavioral features. The presented research will mainly focus on the detection of spam in Urdu reviews; first, it will pre-process the data; then, it will apply feature extraction; and train a classification model; thereby introducing innovative methods to carry out Spam Detections in Roman Urdu Reviews. The results help reduce spam and build confidence in customers regarding the service or product. For this work, we train CNN and LSTM on the given roman Urdu review dataset of Daraz. LSTM outperforms as compared to CNN regarding accuracy. Using models of LSTM we achieved an accuracy score of 97%. Furthermore, we have used a comparative approach using a CNN model that has been tried previously. Nevertheless, these results also tend to suggest that the LSTM model outperforms the CNN model.
INDEX TERMS: Spam Review Detection, Machine Learning, Deep learning.

INTRODUCTION
Spam reviews are fake reviews written by individuals hired by manufacturers/companies to make a profit or promote their products or services. [1]. This practice is also known as review spamming. Any company can hire individuals to write fake reviews of their products and services, such people are called spammers [4]. Recently, this trend of spam attacks has increased because anyone can write spam reviews and post them on e-commerce websites without any restrictions. After reading these positive spam reviews, the user may be motivated to purchase the product, which may otherwise tend to dissuade them. All this shows that spam reviews have become a major problem in online shopping that can lead to loss for both the customer and the manufacturer. Spam reviews can affect businesses financially and can create a sense of distrust in the public. Therefore, this problem has recently attracted the attention of the media and governments. Recent media reports from the New York Times and the BBC state that “spam reviews are very common on websites these days, and recently a photography company was subjected to thousands of customer spam reviews. [4,5]. Thus, the detection of spam reviews appears to be a key area and without solving this important problem, online review sites may become useless to solve this problem, commercial review hosting sites such as Yelp and Amazon have already made

some progress in detecting spam reviews. However, there is still a lot of room for improvement in multilingual review spam detection.

In base paper "Detecting spam product reviews in Roman Urdu script" there are some concerns related to linguistic and spammer behavior features. No one can claim that they are choosing the best features. It totally depends on the problem statement of the specific research. In Proposed work the main aim is to exploit the DARAZ dataset which is taken from the base paper [10]. It contains the reviews in Roman Urdu. The research gap shows that for spam detection linguistic and behavioral features are not fully used, either they use partially or ignored. So, mostly social media in south Asia region is used by the customers in their native language and industries are interested to have spams in Roman Urdu to use this data for effective decision making and marketing strategy. The outcome of this research effectively helps in retaining customer confidence specifically in Pakistan.

A. Contribution

This research in the field of spam review detection add valuable contribution as compare to previous base work [11]. The result shows low score of LSTM due to not enough data to work or train model properly. One of the reasons was class imbalance. To handle and fill this gap we've apply the SMOTE model that balance the data according to target class. It helps in improving the LSTM accuracy. Beside that another contribution is to choose the most appropriate spammer behavioral features. These features were generally handled in base work but in our work linguistic and spammer behavior features are specifically calculate. That provide a deeper insight of the data pattern for spam review detection. Lastly CNN is not applied yet on this data, we've applied it for very first time and then compare the LSTM and CNN results.

B. Paper Organization

The structure of the forthcoming article is outlined as follows: Section II provides background information and reviews existing literature on forgery detection; Section III presents the dataset; Section IV illustrates the experimental setup; Section V introduces the proposed methodology; and Section VI showcases the experimental results.

I. Related Work

Review spam is very common on review websites these days [14]. It has become a challenge for users to detect spam reviews. In addition, there are very few studies that consider multilingual SRD reviews, of which most studies are related to English, Chinese, Arabic, Persian, and Malay. Specifically for the detection of spam reviews in Roman Urdu, most of the work was done between 2017 and 2023.

All the features in Table 1 are practice in the detection of spam in reviews, and each feature gives some specific intuition to detect some spam patterns. RD Rating Deviation: Deviation of the rating of a review from the average rating of the product. Very deviant ratings are primarily fake reviews made to affect the overall product ratings. BRR reflects the number of reviews that appear in a short period, and a high ratio indicates organized spam campaigns. RCS reflects the similarity of the text used in the reviews, and high scores on similarity suggest copies or machine-generated reviews from the same source. CRD reflects how an individual review deviates from its rating from the community average, where significant deviations are the signals to attempt to skew the perception of the products. - CRSP: It calculates the proportion of reviews from users reviewing several stores, such that a higher proportion of reviews is from multi-store reviewers possibly spamming.

PRR: It measures the ratio between the number of reviews that a user makes about different products, and a higher value for this ratio indicates a spammer who has made reviews on many products with a biased intention. PT: It examines the narrow time window or set of specific users who tend to do reviews about a product, where high tightness indicates the coordination between spam activities. Extreme Rating (ER): It is a metric to point out reviews with very high or meager ratings since spammers usually put such extreme ratings just to change the average rating of a product.

Table.1 Spammer behavior features review

Paper ID	RD	BRR	RCS	CRD	CRSP	PRR	PT	ER	MNR	RSP	RFR	RB
[8]	✓	✓	✓									
[18]				✓	✓	✓	✓					
[9]	✓							✓	✓	✓	✓	✓
[5]	✓											
[4]	✓		✓									
[10]	✓						✓	✓	✓			

RD: Rating Deviation, BRR: Burst Review Ratio, (RCS) Review Content Similarity, (CRD) community rating deviation, (CRSP)community reviewed store proportion, (PRR) product reviewer ratio, (PT) product tightness, (ER) Extreme rating, (MNR)Maximum number of reviews, (RSP) Review of a single product, (RFR) The ratio of first reviews, (RB) Review burstiness

Maximum Number of Reviews (MNR): This metric gives the maximum number of reviews any user wrote; generally, spammers have a high MNR and affect many products. A single Product Review (RSP) is if a reviewer wrote just one review for a single product, which sometimes can be pretty suspicious along with other types of spam indicators. The First Reviews Ratio (FRR) measures the case frequency when a reviewer is among the first to review any product. Frequently written reviews in the first person indicate spammers trying to set up initial perceptions. Review Burstiness: It assesses the temporal spread of a review by a user, where high burstiness could indicate reviews in quick succession. For this reason, features like RCS work particularly well in Roman Urdu reviews because language nuances and community dynamics can be invoked by the peculiar linguistic traits of Roman Urdu, which spammers exploit to make such features important in detecting repetitive patterns. These relations, having small language-specific communities, increase the possibility of abnormality in the community's behavior. BRR and other features are showing abnormal activity for the user, which is necessary for detecting group efforts in spamming. RD, ER, and PT are crucial in detecting rating manipulation, which spammers highly desire. Used together, these features can help spam detection algorithms work effectively in flagging suspicious activities and, in turn, maintain the integrity of review systems within Roman Urdu.

Table2: Text Feather Extraction

Paper ID	Bow	TF-IDF	Word2vec	N-gram	Bow weighted by TF-IDF	Classification Algorithm	Accuracy
[15]					✓	SVM	0.80
[11]	✓		✓	✓		BiLSTM	
[20]		✓				Logistic Regression	0.994
[17]	✓					NB, SVM and DT	0.9444

[2]		✓	✓			Naive Bayes (NB), Logistic Regression (LR), SVM	91
[13]				✓		LSTM	77.1

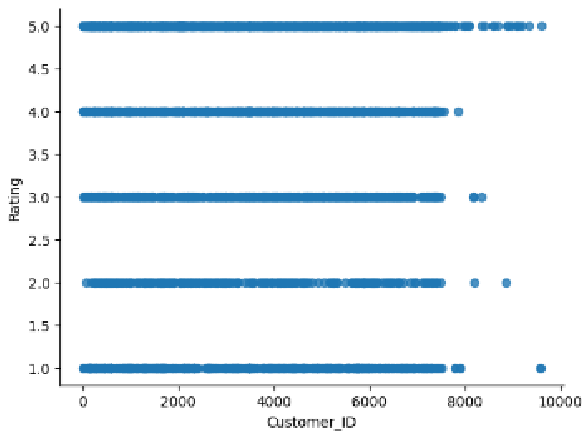
The table summarizes various features extraction techniques and classification algorithms, highlighting their effectiveness through accuracy. N-grams with SVM, achieving 80% accuracy, indicating moderate effectiveness. Combination of Bow, Word2vec, and N-grams with BiLSTM was shown but its accuracy was unspecified. TF-IDF was apply with Logistic Regression, achieving a high accuracy of 99.4%, showcasing significant effectiveness. BoW with NB, SVM, and DT, reaching 94.44% accuracy, demonstrating the strength of ensemble methods. TF-IDF and Word2vec with NB, Logistic Regression, and SVM, achieve 91% accuracy, indicating robust performance. Lastly, Word2vec with LSTM, achieving 77.1% accuracy, showing the potential of neural networks in spam detection. Overall, TF-IDF with Logistic Regression and ensemble methods proved particularly effective.

Many existing studies have worked on the detection of spam reviews in English reviews. He used the Amazon product review dataset and used a linguistic feature to compare the content similarity between the reviews. Moreover, based on content similarity, the proposed method identified spam reviews. They used a logistic regression (LR) classifier to train the model of the proposed method and achieved 78% accuracy [15]. A clustering-based SRD method was present. The proposed method is used to create two clusters of spammers and non-spammers that used the English language revision dataset and achieved 73% accuracy. It used a text-mining model based on time-related features of spammers' behavior. The proposed model used the Yelp dataset and achieved 90% accuracy using linguistic features such as part-of-speech tagging and word count. In addition, the proposed method used a dataset of hotel reviews and achieved 83% accuracy using the linguistic features and behavior of spammers. They used a semi-supervised learning method on a joint training algorithm and achieved 63% accuracy in identifying spam reviews. [16]. A joint training method was used to identify the spam control. They exploited linguistic features such as content similarity using deep learning. Recently there has been a development in [19][21] regarding aspect-based spam review detection that is another way to differentiate spam and not spam review.

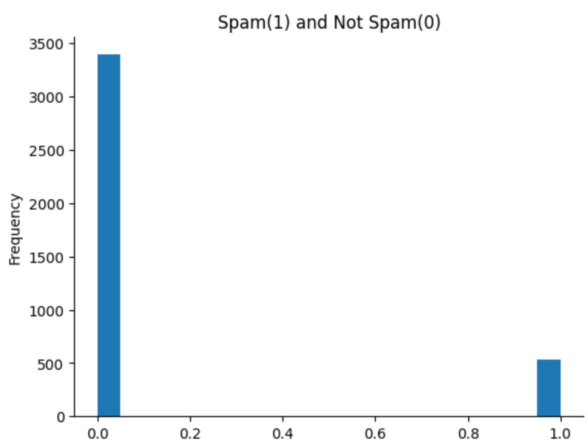
So, to the best of our knowledge, there does not exist any detailed and comprehensive study to analyze SRD in Roman Urdu reviews. Therefore, there is a need to develop reliable and accurate SRD methods using Roman Urdu reviews. In this section, existing literature has been analyzed to explore the SRD methods using multilingual review datasets.

II. Dataset

Daraz is on of the famous and largest Pakistan's e-commerce platform. It boasting an extensive catalog of over 2 million products. It has a network of 30,000 sellers. It also has a loyal customer base exceeding 5 million individuals. This research initiative curated a comprehensive Daraz dataset encompassing product reviews spanning the period from February 2016 to March 2019. Notably, the dataset comprises 2976 reviews penned in Roman Urdu, covering a diverse array of 10 distinct product categories. Eight attributes: Product ID, Category ID, Customer Name, Customer ID, Date, Review title, Review text and Rating.
https://www.kaggle.com/datasets/naveedhn/daraz-roman-urdu-reviews.
Following is the detail of dataset
Product Categories Review: Tablets & phones, Clothing & fashion, Beauty & health, Appliances, Computers & gaming, TV, audio & cameras, Home & living, Sports & travel, Baby, toys & kids, Grocery
Total Reviews: 2976
Total Reviewers: 957
Total Products:199
This dataset was not labeled but in [] it was labeled with the help of Yelp dataset.
Following figures are showing distribution of



Figur.1 Rating vs customer_ID



Figur.2 Frequency vs spam (1) and not spam (0)

III. Experimental set up

Google Colab is a cloud-based platform. It is extensively use to conduct spam review detection on Roman Urdu text. Following are details of the experimental setup. it utilize Python 3 programming language. Powerful machine learning libraries such as Keras and scikit-learn. Matplotlib and seaborn for plotting of charts and visualization. Due to resource constraints CPU hardware accelerator provided by Google Colab is use. The dataset discusses in [10] is comprised a collection of product reviews written in Roman Urdu. It is spanning various categories and sourced from the Daraz e-commerce site. Preprocessing involves tokenization, normalization, and feature extraction. Then balancing class to prepare the text data for training. CNN and LSTM are individually apply with or without feature selection. This experimental setup facilitated efficient development and testing of spam detection models on Roman Urdu text.

IV. Preprocessing

Following is the detail of preprocessing steps involved in experiment i.e. Data Cleaning, Tokenization, Stop word removal, The addition of these features allows for efficient data handling and manipulation, supporting the development of advanced models for distinguishing between spam and not spam features. This preprocessing step is a critical aspect of the research, setting the stage for detailed examination and contributing to the broader field of spam review detection using Roman Urdu text.

Data Cleaning: In data cleaning phase, all duplicate messages are removed and only distinct messages are part of the dataset. All special characters, links, emoji's, punctuation symbols or anything, that has nothing to do with fraud detection, are removed from each instance of dataset.

Tokenization: Tokenization is a common and essential technique in natural language processing. It involves breaking down the text into individual words or "tokens." For instance, the sentence "The product is amazing" would be tokenized into ["The", "product", "is", "amazing"].

Stop words Removal: Stop words are the words that has nothing to do in classification process. By removing stop words, we can save space and enhance the efficiency of our model [15]. The examples of stop words in English language are: "if", "and", "or", "the" etc. Because all instances in our dataset are in Roman Urdu and there is not any dataset available of Roman Urdu stop words so we created a manual stop word text file which contains the Roman Urdu stop words. Some of the examples of Roman Urdu stop words are: "aur", "par", "lekin" etc.

C. Remove Class Imbalance

SMOTE (Synthetic Minority Over-sampling Technique) is a data augmentation method commonly used to address class imbalance in machine learning tasks. By generating synthetic samples for the minority class, SMOTE helps improve the classifier's ability to learn from imbalanced datasets, thereby enhancing model performance and reducing bias towards the majority class. The data was not equally distributed so results are show below how smote helps in balancing the data

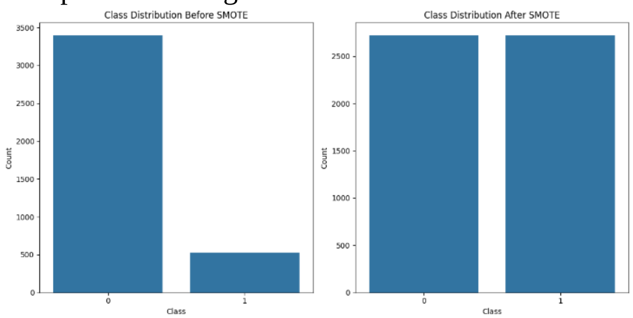


Figure.**Error! No text of specified style in document.**3 SMOTE FOR CLAA BALANCE

SMOTE Algorithm

1. **For each minority class sample x_i:**
   - Find its k-nearest neighbors from the same class.
2. **For each neighbor x_{ij} (where j ranges from 1 to k):**
   - Generate a new synthetic sample x_{new} as follows:

$x_{\text{new}} = x_i + \delta \times (x_{ij} - x_i)$

where δ is a random number between 0 and 1.

D. Linguistic and spammer behavior Feature Extraction

E. TF-IDF

It is commonly used to extract the linguistic features in the spam review detection. It is a statistical method that evaluates the importance of a word in document relevant to the corpus of documents.it is particularly used in text classification tasks.

Term-Frequency: measures how frequently the terms appear in the document. The frequency increase the proportionally to the number of times a word appears in the text.

Invers Document Frequency: measures how important a term is.

- **TF:**
  $$\mathbf{TF}(\boldsymbol{t},\boldsymbol{d})\frac{\textbf{Number of times term } \boldsymbol{t} \textbf{ appears in document } \boldsymbol{d}}{\textbf{Total number of terms in document } \boldsymbol{d}}$$
- IDF:
  $$\mathrm{IDF}(\boldsymbol{t},\boldsymbol{D})\boldsymbol{log}\frac{\text{Total number of documents in corpus } \boldsymbol{D}}{\text{Number of documents containing term } \boldsymbol{t}}$$
- **TF-IDF:** $\mathbf{TF\text{-}IDF}(\boldsymbol{t},\boldsymbol{d},\boldsymbol{D}) = \mathbf{TF}(\boldsymbol{t},\boldsymbol{d}) \times \mathbf{IDF}(\boldsymbol{t},\boldsymbol{D})$

Linguistic and spammer behavior feature are calculated and use as input for model training. The general correlation of different features in dataset is shown in the following correlation heat map figure.

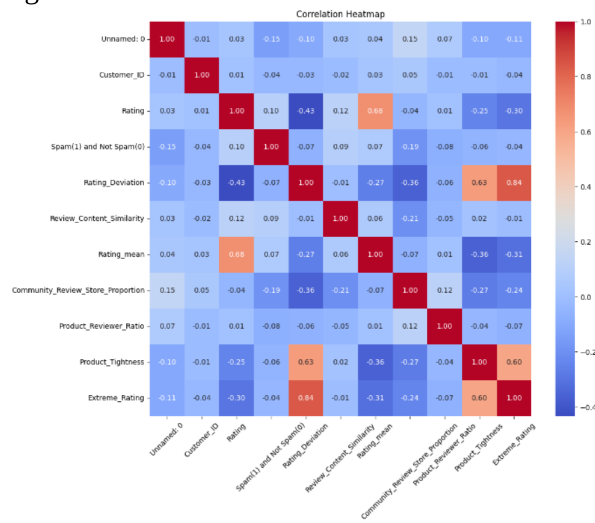


Figure.4 Dataset features correlation heat map

Feature Selection

Input: Processed_Reviews
Output: Spammer_Behaviour_Features

Step 1: for each review in Processed Reviews **do**

for each spammer behavior feature Fi calculate normalized value using distribution **do**
    calculate normalize value of Fi

    end **for**
end **for**

Feature extraction is vital for enhancing the accuracy of machine learning models. By identifying and selecting the most relevant features, this step reduces the dataset's size and complexity. The refined features are then used as inputs for machine learning and deep learning models, making the data more meaningful and efficient for analysis.

F. Methodology

Preprocessing and Section C shows all detail of initial steps of methodology. After 80:20 data split for testing and training LSTM and CNN is apply individually.

Following Algorithm shows the proposed methodology step by step.

Spam Review Detection using Roman Urdu Reviews

```
Input: Roman Urdu Reviews
Output: Spam(1) or Not Spam(0)
Step 1: apply preprocessing for roman urdu reviews
Step 2:apply Smote
Staep3: Feature selection
    for each review in Processed Reviews do
        for each spammer behavior feature Fi calculate normalized value using distribution do
        calculate normalize value of Fi
        end for
    end for
Step 4: Feature reduction
Step5: Classification
        Initialize x and y do split
        //x-train,y-train & x-test, y-test
    fit.model //[LSTM, CNN]
        if target==1
          return spam
        Else
        return not spam
    End
```

This is the simplest model for spam review detection using roman Urdu reviews.

V. Results

In this section first proposed methodology results are shown. For evaluation of results Precision, Reall and F1 score was use.

Precision shows that the predicted spam reviews are indeed spam. It is important to maintain the user trust and integrity of the review plate form.

P=TP/(TP+FP)

Recall ensures that most of the spams are detected and reduce the chances to slip buyer through such spam reviews.

R=TP/(TP+FN)

F1-Score consider both false positive and false negative that provides a balance metrics to show the model performance in spam review detection.

F1 SCORE = 2*(P*R)/(P+R)

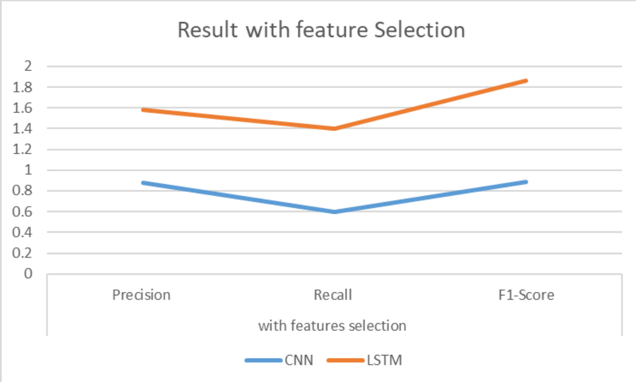
Discuss results apparently states that LSTM work in a best manner and beat the CNN in Spam detection using roman Urdu spam text.

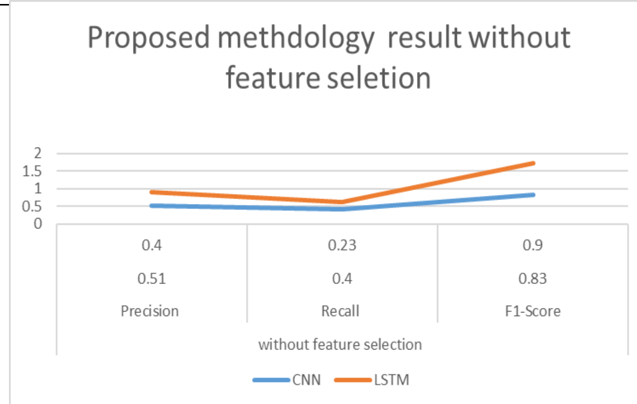
Table.3 Results

	With Feature selection			Without feature selection		
	Precision	Recall	F1-score	Precision	Recall	F1-score
CNN	0.88	0.6	0.89	0.51	0.4	0.83
LSTM	0.7	0.8	0.97	0.4	0.23	0.90

Feature selection plays and important role and as it was discuss earlier that in spam review detection linguistic and spammer behavior features are not fully exploit. That may ignored or partially apply. Proposed methodology try to apply both linguistic and spammer behavior features simultaneously. It analyzed its impact on ML models. As shown in above table.

Following figures shows that feature selection helps in improving the accuracy of both CNN and LSTM model.





this section compare the results of proposed methodology with base paper results to show how a change feature selection method and preprocessing steps can change the ML models result authentication.

this section compare the results of proposed methodology with base paper results to show how a change feature selection method and preprocessing steps can change the ML models result.

Table. 4 Result comparison with base paper

	Proposed Result [with features selection]			Base Paper [10] Result [with feature selection]		
	Precision	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
CNN	0.88	0.6	0.89	N/A	N/A	N/A
LSTM	0.7	0.8	**0.97**	0.668	0.784	0.721
Random forest				0.951	0.952	0.952
Bernoulli Naive Bayes				0.909	0.898	0.904
Logisticregression				0.879	0.935	0.906

Table clearly states that LSTM this time performs well. For avoiding overfitting, we have used Smote to balance the class. It helps LSTM to improve its results. While CNN was not discussed in base paper. In proposed work CNN shows a low score when compare to LSTM. It shows that CNN can compromise its score while used for Roman Urdu.

Conclusion

Research indicates that SRD is a serious and problematic issue. Additionally, the SRD issue in Roman Urdu reviews is not fully examined. This study evaluates the Roman Urdu review dataset using ML classifiers. Linguistic and spammer behavioral aspects are analyzed in proposed work. N. Hussain et al. analyzed Roman Urdu reviews from daraz.pk. Existing research indicate this is the first study to examine classifier performance employing linguistic and converted spammer behavioral variables on a real-world Roman Urdu review dataset. Experimentation shows that integrating linguistic and behavioral factors enhances the F1 score. The assessments indicate that the LSTM outperforms than CNN. Though this work is at its initial stage but another future project is to use location-dependent spammer behavioral traits to detect and review spammers. The study of spammer groups writing spam reviews in Roman Urdu review databases is a promising future research topic. Additionally, comparing deep learning models on a large Roman Urdu review dataset might be a promising study path for spam review identification.

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