SENTIMENT ANALYSIS FROM URDU LANGUAGE-BASED TEXT USING DEEP LEARNING TECHNIQUES

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PLAGIARISM SCAN REPORT



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Sentiment Analysis from Urdu Language-based Text using Deep Learning Techniques

I. ABSTRACT

The Internet has seen substantial growth of domestic language data in recent times. It enables people to express their opinion by incapacitating the language walls. Urdu is a language used by170.2 million people for communication. Sentiment analysis is used to get sapience of people opinion. In recent times, experimenters' interest in Urdu sentiment analysis has grown. Operation of deep literacy styles for Urdu sentiment analysis has been least explored. There's a lot of ground to cover in terms of textbook processing in Urdu since it's a morphologically rich language. In this paper, we propose a frame for Urdu Text Sentiment Analysis (UTSA) by exploring deep literacy ways in combination with colorful word vector representations. The performance of deep literacy styles similar as Long Short-Term Memory(LSTM), 1D- Convolutional Neural Networks(CNN) IS estimated for sentiment analysis. piled layers are applied in successional model LSTM, In CNN, we used single complication subcaste. part of pre-trained and unsupervised tone- trained embedding models is delved on sentiment bracket task. The results attained show LSTM works good on this data and achieved the delicacy of 83 percent.

II. INTRODUCTION

With the invention of internet many fields have gain a lot of attention in the modern days. In social media applications like Facebook, Twitter etc. People post a lot of comments. According to statistics there are 4.66 billion active internet

users till October 2020. Many studies have been conducted in English to study the sentiments of people.

Sentiment analysis is a term used to extract subjective information by applying Natural Language Processing technique. It is used to classify tax as positive, neutral or negative regarding a product service topic event etc.

It can be applied at document level, sentence level or aspect level. There are three kinds of approaches being used:

- Lexicon-based approach,
- Machine learning based approach and
- Deep learning-based approach.

In the study we have utilized publicly available IDBM datasheet which contain 50000 reviews and we have applied different machine learning and deep learning approaches to check the accuracy of our models.

III. METHODOLOGY

A. Dataset

we have taken publicly available dataset on Kaggle named as IMDB Dataset of 50K Movie Reviews. This dataset contains two files train and test csv files, having two columns named as reviews and sentiment. We have now 50,000 records available in our dataset

train_data = pd.read_csv("/kaggle/input/imdb-dataset-of-50k-movie-translated-urdu-rev
test_data = pd.read_csv("/kaggle/input/imdb-dataset-of-50k-movie-translated-urdu-revi

train_data.head(), test_data.head()

```
review sentiment
review sentiment ... میں نے اسے 80 کی ببائی کے وسط میں ایک کیل گائی 6 ... positive
regative ... میں نے اسے 80 کی ببائی کے وسط میں ایک کیل گائی 10 ... positive ... positive ... positive ... positive ... مید اللہ گئی ہے ۔.. مید اللہ کے بارے میں انہیں کہ ٹوکری 3 ... positive ... positive ... positive ... positive ... positive ... positive ... review sentiment ... بہ ہے گیر خراتین کے بارے میں ایک میشاروزی ظم 0 ... negative ... negative ... negative ... negative ... positive ... positive ... positive ... positive ... positive
```

fig 1.1: Dataset Preview

B. Distribution of data

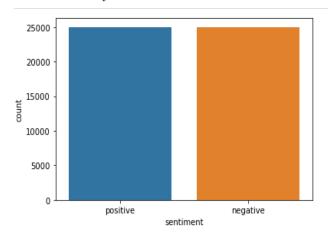


Fig 1.2
We can see that there are only two classes in our dataset:

- Positive means the review holds positive sentiment.
- Negative means the review holds negative sentiment.

Also, the class is very balanced. So, it will be easy for us to build any model.

C. Preprocessing

For this purpose, we used Urdu Hack library in python which provide extensive features to work Urdu language. First of all, our dataset contain train and test csv files and we merge them to make a single file. Then we have applied labeled encoding to label our sentiment columns.

Then we applied the following preprocessing to review columns to clean our data. After that we removed the stop words and lemmatized the reviews Now, we are ready to apply different deep learning approaches.

IV. MODEL ARCHITECTURE:

A. Machne Learning Models:

1) TF - IDF Vectorization

TF-IDF is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. This is done by multiplying two metrics: how many times a word appears in a document, and the inverse document frequency of the word across a set of documents.

We split the dataset into training, test sets. Then we trained following models and check their accuracy

- Support Vector Machine Classifier
- Logistic Regression Classifier
- Decision Tree Classifier
- Xgboost Classifier
- Random Forest Classifier

B. Deeep Leaning Models

For deep learning approaches, we have used Spacy library to tokenize our data, then we prepared word to vector Model

1) Word to Vector Model

Word2Vec consists of models for generating word embedding. These models are shallow two-layer neural networks having one input layer, one hidden layer and one output layer.

After that we implemented embedding layers then we train our two models

- 1D-CNN
- LSTM

V. RESULTS

A. Machine Learning Models

Finally, in order to further evaluate the performance of these models, the accuracy, precision, recall, and F1-score metrics are calculated and compared in. These performance metrics are briefly introduced as follows

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F - measure = \frac{2*Recall*Precision}{Recall + Precision}$$

Now we will provide the result of different algorithms that we have mentioned above.

	M CLASSIFIER	on IF-ID	F Vectorize	er
	precision	recall	f1-score	support
0	0.86	0.87	0.86	7408
1	0.87	0.86	0.87	7592
accuracy			0.86	15000
macro avg	0.86	0.86	0.86	15000
eighted avg	0.86	0.86	0.86	15000
[6421 987] [1049 6543]]				

Fig 5.1 SVM

Results of Logistic Regression Classifier on TF-IDF Vectorizer

	precision	recall	f1-score	support	
0	0.86	0.88	0.87	7350	
1	0.88	0.87	0.87	7650	
accuracy			0.87	15000	
macro avg weighted avg	0.87 0.87	0.87 0.87	0.87 0.87	15000 15000	
weighted avg	0.07	0.07	0.07	13000	
[[6444 906]					

[1026 6624]]

Fig 5.2 Logistic Regression

Results of Decision Tree Classifier on TF-IDF Vectorizer

	precision	recall	f1-score	support	
	•				
0	0.56	0.81	0.66	5220	
1	0.87	0.67	0.75	9780	
accuracy			0.72	15000	
macro avg	0.72	0.74	0.71	15000	
weighted avg	0.76	0.72	0.72	15000	
[[4218 1002]					
[3252 6528]]					

Fig 5.3 Decision Tree Classifier

J				
	precision	recall	f1-score	support
0	0.74	0.82	0.78	6731
1	0.84	0.76	0.80	8269
accuracy			0.79	15000
macro avg	0.79	0.79	0.79	15000
weighted avg	0.79	0.79	0.79	15000
[[5517 1214] [1953 6316]]				

Fig 5.4 Xgboost Classifier

Results of Random Forest Classifier on TF-IDF Vectorizer

	precision	recall	f1-score	support	
0	0.80	0.85	0.82	7072	
1	0.86	0.81	0.83	7928	
accuracy			0.83	15000	
macro avg	0.83	0.83	0.83	15000	
weighted avg	0.83	0.83	0.83	15000	
[[5989 1083] [1481 6447]]					

Fig 5.5 Random Forest

B. Sentiment Analysis using Word to Vector and Deep Learning

	precision	recall	f1-score	support
0.0	0.85	0.84	0.85	5084
1.0	0.84	0.85	0.84	4916
accuracy			0.85	10000
macro avg	0.85	0.85	0.85	10000
weighted avg	0.85	0.85	0.85	10000

Fig 5.6 Confusion Matrix of 1D-CNN

	precision	recall	f1-score	support
0.0	0.85	0.87	0.86	4928
1.0	0.87	0.85	0.86	5072
accuracy			0.86	10000
macro avg	0.86	0.86	0.86	10000
weighted avg	0.86	0.86	0.86	10000

(Shabbir)

Fig 5.6 Confusion Matrix for LSTM

VI. CONCLUSIONS

We have preprocessed the text data using Urduhack library and applied multiple algorithms on this dataset and achieved maximum accuracy of 87 percent using Logistic Regression. we have achieved 88 percent accuracy using SVM without Urdu Hack but after preprocessing using Urduhack the accuracy falls down. So, we can conclude that the Urduhack text processing preprocess the text quite well but also affects the accuracy.

Then we build the Word to Vector embeddings and build deep learning models. We build 2 models, LSTM and Convolutional Network and compare their results and noticed that the LSTM works good on this data and achieved the accuracy of 83 percent. We also achieved the same accuracy with ConvNet but LSTM is more stable in results.

VII. FUTURE WORK

In coming days, we will also build Glove Embeddings for this data and train Deep Learning Models.

VIII. REFERENCES

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We can see that there are only two classes in our dataset: Positive means the review holds positive sentiment. Negative means the review holds negative ...

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Then we build the Word to Vector embeddings and build deep learning models. We build 2 models, LSTM and Convolutional Network and compare their results and ...

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