Apprehension Of Spurious Information – A Hybrid Architecture to Detect Fake Information Using Natural Language Processing

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INTRODUCTION

- With the rapid growth of Internet it is undebatable that we are able to communicate and access information as a faster pace.
- Nevertheless, the same tool can have a negative impact if the information we share or receive is fraudulent.
- Propagation of false information has an enduring effect on the economy and can lead to political tensions too.
- In order to counterattack this unexpected repercussion, a system needs to be modeled to distinguish the hoax from the real.

OBJECTIVES

- To design and develop a **hybrid architecture** which classifies the input information as Fake or Real.
- Explore the suitable **architectures for the decoder** of the model, having a CNN encoder.
- Understand the working of **different word embeddings** and identify the one with the optimal performance.

DATASET

Covid Fake News Dataset

[Link to Covid Fake News Dataset]

- Has social media posts and articles of real and fake news on COVID-19.
- Attributes include id, tweet and label.
- Composed of 6843 records .
- Two possible output classes - Fake and Real.

Disaster Tweets Dataset

[Link to Disaster Tweets dataset]

- Aims to determine if the information is about a real disaster or not
- Attributes include id, keyword, location, text and target
- Composed of 7613 records
- Two possible output classes - Fake and Real.

DATASET

ISOT Dataset

Link to ISOT Dataset

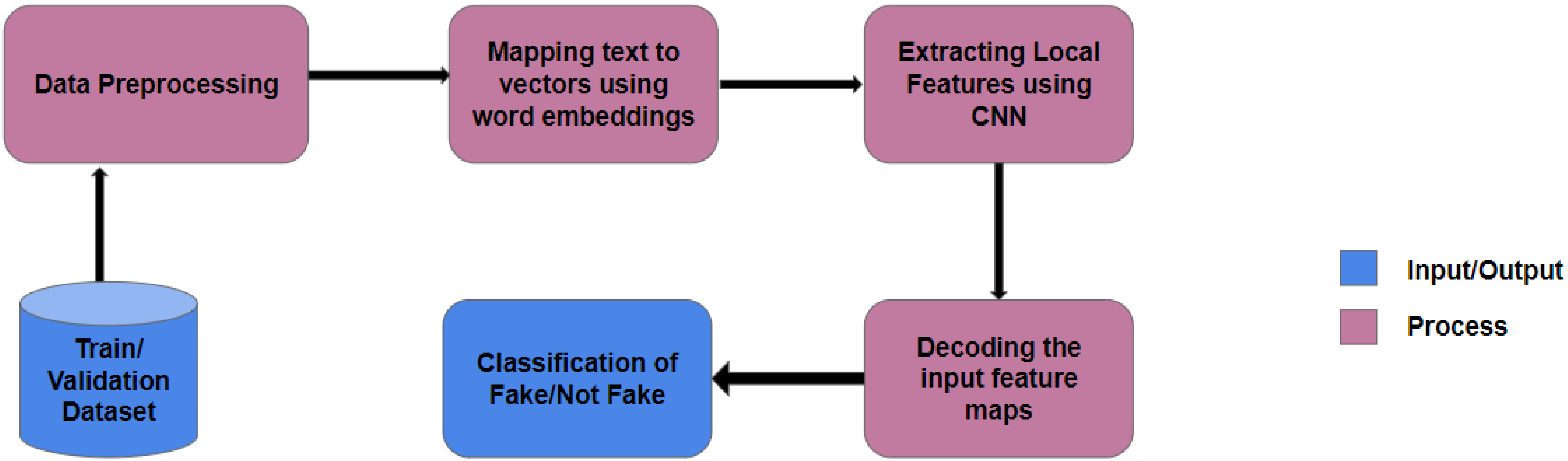
- Compilation of thousands of fake and real news.
- Attributes include title, text, subject and date.
- Composed of 47000 records .
- Two possible output classes - Fake and Real.

LIAR Dataset

Link to LIAR dataset

- Has manually labelled short sentences collected from politifact.com for fact checking research
- Attributes include id, label, statement, subject, speaker.
- Composed of 12800 records
- Two possible output classes - Fake and Real.

BLOCK DIAGRAM



Reference: Jamal Abdul Nasir, Osama Subhani Khan, Iraklis Varlamis, Fake news detection: A hybrid CNN-RNN based deep learning approach, International Journal of Information Management Data Insights, Volume 1, Issue 1,2021,100007,ISSN 2667-0968,https://doi.org/10.1016/j.jjimei.2020.100007.

PERFORMANCE

Covid Fake News Dataset *(Accuracy in %)*

Embedding Used	LSTM		Bi-LSTM		GRU		Bi-GRU	
	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout
Keras Embedding	89.38	90.05	89.88	89.55	89.21	89.8	89.8	90.05
Word2Vec	*89.46*	*89.21*	*88.55*	*89.88*	*90.55*	*88.7*	***90.05***	***89.8***
Glove50D	85.98	85.2	84.74	85.12	85.98	86.21	85.67	85.59
Glove100D	84.9	83.5	85.2	84.1	84.6	84.1	84.6	85.8
BERT	88.7	90.2	88.6	90.5	90.25	89.7	87.5	89.4

Disaster Tweets Dataset *(Accuracy in %)*

Embedding Used	LSTM		Bi-LSTM		GRU		Bi-GRU	
	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout
Keras Embedding	78.56	78.85	77.67	79.12	79.77	78.92	78.79	79.25
Word2Vec	77.08	76.89	76.17	77.94	79.25	74.92	78.99	73.74
Glove50D	*79.91*	*79.51*	*78.98*	*80.5*	*79.45*	*80.17*	***80.17***	***80.11***
Glove100D	78.86	79.12	79.45	79.65	78.46	79.97	79.84	80.04
BERT	78.2	78.4	77.22	77.87	77.94	76.23	78.59	79.71

PERFORMANCE

LIAR Dataset *(Accuracy in %)*

Embedding Used	LSTM		Bi-LSTM		GRU		Bi-GRU	
	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout
Keras Embedding	64.53	64.91	64.61	64.23	61.57	63.62	64.38	64.84
Word2Vec	64.38	64.38	64.38	64.38	64.4	64.38	64.38	64.38
Glove50D	64.69	61.11	65.45	65.53	65.22	63.47	**65.44**	**67.05**
Glove100D	64.01	63.8	64.9	64.8	63.7	63.5	66.01	62.08
BERT	64.08	62.8	62.9	65.5	64.6	64.8	66.47	66.02

ISOT Dataset *(Accuracy in %)*

Embedding Used	LSTM		Bi-LSTM		GRU		Bi-GRU	
	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout	With Dropout	No Dropout
Keras Embedding	95.41	96.4	95.95	95.67	96.3	95.31	96.16	95.78
Word2Vec	98.92	98.47	98.83	98.74	98.86	98.31	98.52	98.62
Glove50D	98.08	98.91	99.01	98.9	98.96	98.86	**98.99**	**99**
Glove100D	96.2	95.62	95.68	96.25	96.02	95.88	96.24	96.46
BERT	98.8	98.8	98.9	98.5	98.3	98.2	98.99	98.8