BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE, PILANI

March-April 2022

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For fulfilling the

partial requirement of

CS F469: Information Retrieval

Structure of the report (Left)

4. Research Gap (optional)

7. Experimental Results and evaluation: Present your results and evaluation of your system a. For example, if your problem is information retrieval then present different queries and their retrieved results and ranking. b. Present some results that show the goodness of the retrieved results e.g., precision, recall, F1-measure, NDCG, etc. along with ground truth.

8. Conclusion and future work

9. References

Problem Statement

To detect fake news using a hybrid Neural Network architecture, that combines the capabilities of CNN and LSTM, which is further used with two dimensionality reduction algorithms, Principle Component Analysis (PCA) and Chi-Square. And report the results with relevant Evaluation Criteria so as to show the competitiveness of the model chosen.

Background of the Problem

a. Description of the selected application domain

Fake news's simple meaning is to incorporate information that misleads people to believe an untrue fact. Nowadays, with the prevalence of social media and easy access to a lot of information, fake news spreads like water and people share this information without verifying it. So, it is an important task to detect fake news and convey the results in negligible time.

In the long run, a lot of machine learning models have been developed and deployed to detect fake news, these machine learning models can be classified into-

- Supervised learning
- Unsupervised learning
- Reinforcement learning

b. Motivation of the problem

As humans, satiety in the current models and accuracy achieved isn't possible and we keep on trying new models to solve the problem. The idea of applying CNN and LSTM as a hybrid comes from the fact that the authors compared the effectiveness of the feature reduction based methods used with two deep learning models i.e. CNN and LSTM. The experimental results indicate that the proposed model improves the F1-score and accuracy by 20% and 4% respectively when used with the reduced feature set, than the other techniques discussed in the related work section.

c. Technical issues included in your work

RAM issues were faced while running the dataset, and even if we try to reduce the training data to get a possible result, the same issues are faced on personal systems as well as online servers. The model had been set up early on and was ready for implementation but we were unable to get the results immediately.

Literature Review

Fake news is one of the most recent and pressing issues. With the exponential growth in the amount of data collected each day and the increasing popularity of social media platforms such as Twitter, Facebook, and Instagram, information communication has gotten exponentially easier and faster. This highlights the critical nature of assessing the veracity of news articles. The implications of widespread incorrect information are becoming increasingly detrimental, ranging from business and stock market disruption to influencing presidential elections.

Stance Detection

Numerous studies have attempted on how to efficiently integrate automatic stance evaluation utilizing natural language processing to aid in the process of fact checking and improve the detection of fake news. According to J. W. Du Bois, stance-taking is a subjective and interpretative phenomenon influenced by both personal and private elements such as societal traditions. Taking a stance is a complex process that involves a variety of personal, cultural, and societal factors. NLP tools are used to figure out how similar the headline and body text are in terms of both semantic and contextual similarity. They then put the pairs into one of four groups. All deep models are constructed using recurrent networks, such as recurrent neural networks (RNN), long short-term memory networks (LSTM) , and gated recurrent units (GRU), as well as convolutional networks, such as convolutional neural networks (CNN). A deep architecture encodes a given series of words into a fixed length vector representation, which may then be used to score the relevance of two or more words in a sequence of words. In our context, the relevance of each headline-body pair. Fake news identification, claim validation, and argument search have all relied on Stance detection as a foundation.

FNC-1 detects stance at the document level, classifying the entire news story in relation to a headline. The stance may be labelled as "agree," "disagree," "discuss," or "unrelated." The FNC-1 challenge dataset was partially annotated and was derived from the Emergent dataset. All news containing the terms "agree," "disagree," and "debate" are deemed to be "related." A Gradient Boosting classifier with a relative score of 75.20 percent is used as the FNC-1 official baseline. This classifier employs semantic analysis and the crossover of headlines and body text.

This classifier employs semantic analysis and the crossover of headlines and body text. For the FNC-1 submissions, the best detection performance is achieved using an ensemble of convolutional neural networks and gradient-boosted decision trees. A somewhat less accurate performance is found in a five multi-layer perceptrons (MLP) ensemble. Both of these methods take in information from semantic analysis, a bag of words, and baseline features. The third system is not ensemble-based but rather a "simple yet difficult to beat baseline" approach. Their end-to-end stance identification system utilizes lexical and similarity characteristics that are fed into a multi-layer perceptron (MLP) with a single hidden layer. Team number four takes both lexical matching and semantic embedding features from the text, and then trains another gradient boosting tree to improve its results. All of the methods discussed employ classification-based algorithms to determine stances, with the goal of approximating the true probability distribution of the four stances in news stories.

Existing approaches for detecting fake news

The network mode method: It verifies the claims made in news or articles and determines if they are true or false in terms of the validity of the claims made in the report using network analysis. This method can employ a variety of fact-checking techniques, including expert-based, crowdsourcing, and computational fact-checking.

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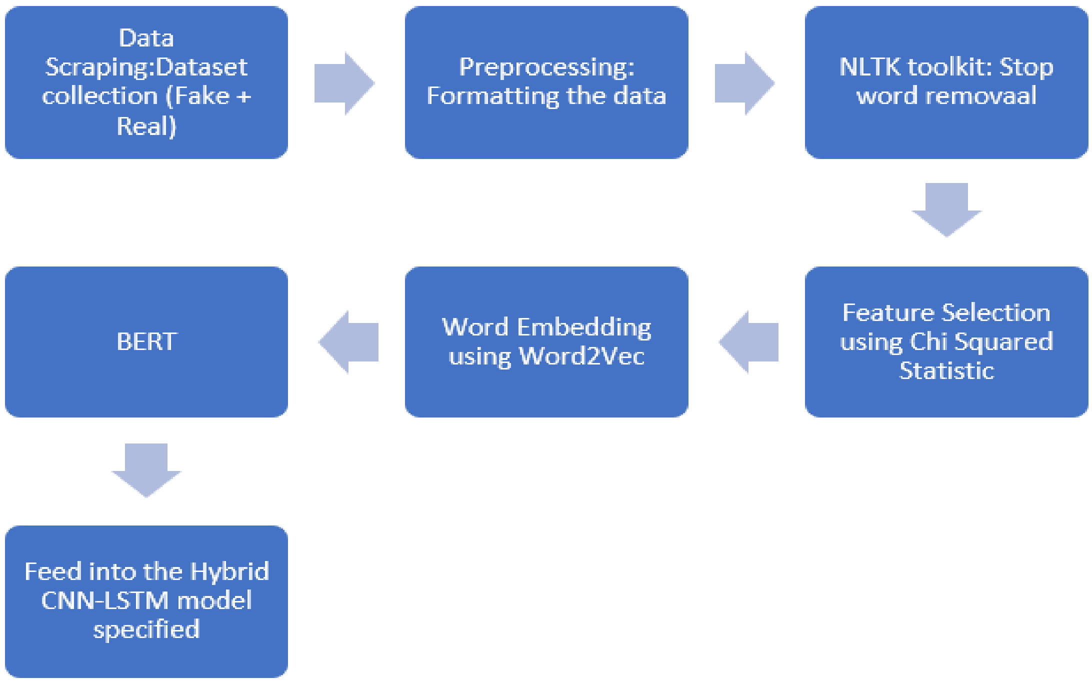
Naive Bayes Classifier: Bayes' Theorems are used to derive Naive Bayes classifiers. These methods estimate the likelihood of a given event occurring in a given system based on the fact that something similar has already occurred. As a result, they can predict the likely conclusion of any event by studying the preceding events. This is the machine language structure. The technique of Naive Bayes' classifiers is a simple and straightforward one. The most significant disadvantage of naive Bayes' classifiers is that it decides all of the characteristics separately, which would be confusing for this technique and might result in a reduction in the ability to determine the news due to a lack of coordinated investigation.

Support vector network (SVN): The terms support vector machine (SVM) and support vector network (SVN) are equivalent. Support Vector Machines employ an advanced learnable algorithm. The programmer trains these algorithms to acquire special skills. SVMs function only once they have been trained and have gained a special expertise. This method classifies the data and also optimizes the margin between the columns of two data columns that are accessible . It is a highly precise model of analysis, and in addition to being more flexible, this method is capable of determining numbers and dealing with multi-dimensional storage spaces.

System Description



The dataset is first collected from the Fake News Challenge's official website. The dataset has multiple Labels which are -

LABELS

3 - Agree: There is a relation between headline and article body.

1 - Disagree: There is no relation between headline and article body.

2 - Discuss: There is a little bit of match between headline and article body, taking it as neutral.

0 - Unrelated: The topic discussed in headline and body are completely different.

Furthermore, we go ahead to pre-processing the data, which is basically processing the data into a format which is standard and can be fed to any algorithm going further.

The pre-processed data is then subjected to nltk library's processing, where the words are further stemmed, tokenized and lemmatized. Further a few more data cleaning algorithms are written for specific exceptions in the dataset, and then the text is converted to a word sequence.

Now feature selection is done using chi squared statistics to reduce the dimensionality of the data and the top 200 features are selected.

After this word vectorization is done using the word2vec library, an embedding is created using the same, a sample of the same is

```
[array([-1.8953801 , -0.17797464, -2.8194003 ,  0.07569357,  1.3593788 ,
         0.13766855,  1.4326755 , -0.7237559 , -1.4765378 ,  0.30202305,
        -1.7503111 , -1.7832469 , -0.07237303,  1.4765407 , -1.6647637 ,
         0.13704908,  0.4430769 ,  0.2952515 , -0.7405423 , -1.3794237 ,
        -2.2561543 ,  0.94514626,  0.21605526, -0.55671024, -1.6020415 ,
```

We introduce a new language representation model called BERT, which stands for Bidirectional Encoder Representations from Transformers.

Unlike recent language representation models, BERT is designed to pre-train deep bidirectional representations by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT representations can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

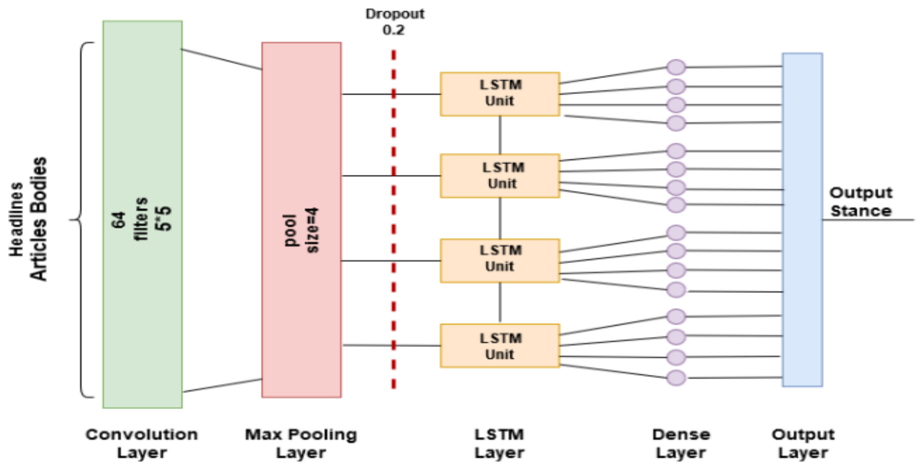
BERT is conceptually simple and empirically powerful.

It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE benchmark to 80.4% (7.6% absolute improvement), MultiNLI accuracy to 86.7 (5.6% absolute improvement) and the SQuAD v1.1 question answering Test F1 to 93.2 (1.5% absolute improvement), outperforming human performance by 2.0%.

BERT Results are as follows-

Layer (type)	Output Shape	Param#
embedding_3 (Embedding)	(2240,100)	500000
dropout_3 (Dropout)	(2240, 100)	0
conv1d_3 (Conv1D)	(2236, 64)	32064
max_pooling1d_3 (MaxPooling1D)	(559, 64)	0
lstm_3 (LSTM)	(100)	66000
dense_3 (Dense)	(4)	404

Further the hybrid CNN-LSTM model is set up to implement the model specifications in the paper chosen, the specifications can be best understood via the diagram below. And the processed data is put through the model to get the results.



Evaluation Strategy:

To compare and evaluate our model, we use accuracy (A), precision (P), recall (R), and F1-score (F) as evaluation metrics.

Precision is calculated as the ratio of correctly classified positive class and the sum of correctly and falsely classified values of the positive class. It tells us about the factualness of the model.

$$P = (\text{True Positive}) / (\text{True Positive} + \text{False Positive})$$

A recall rate is calculated as the ratio of correctly classified positive class and the sum of correctly classified values of the positive class and falsely classified values of the negative class. It tells us about the completeness of the model.

$$R = (\text{True Positive}) / (\text{True Positive} + \text{False Negative})$$

F1-score determines the accuracy of the model for each class. The F1-score metric is usually used when the dataset is imbalanced. As the dataset of FNC-1 is also highly imbalanced therefore, to calculate the class-wise accuracy, we use F1-score as evaluation metrics to show the completeness of the proposed model.

$$F1 = 2 * (\text{precision} \cdot \text{recall}) / (\text{precision} + \text{recall})$$

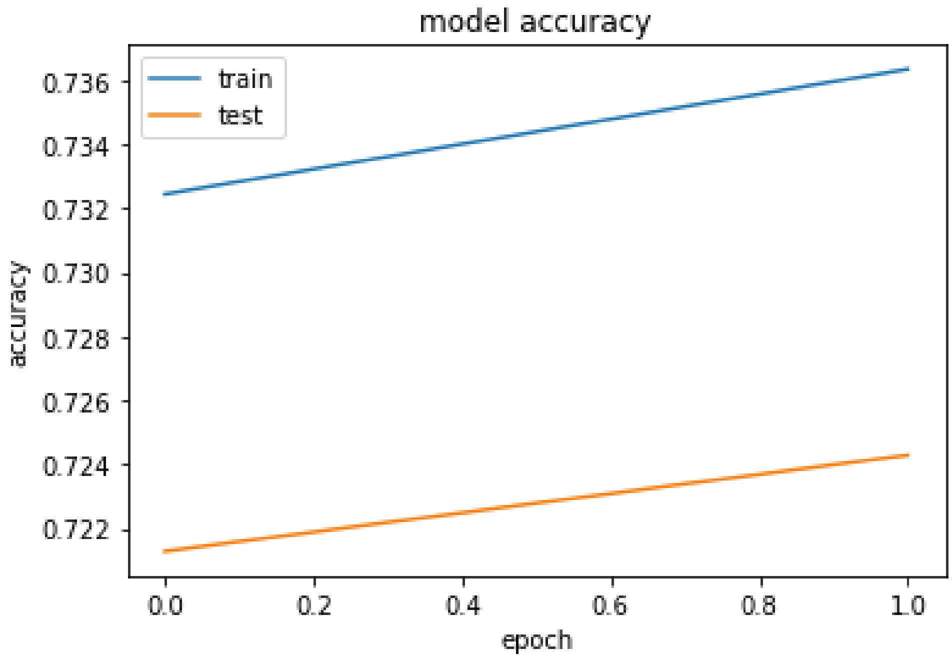
Experimental Results and evaluation:

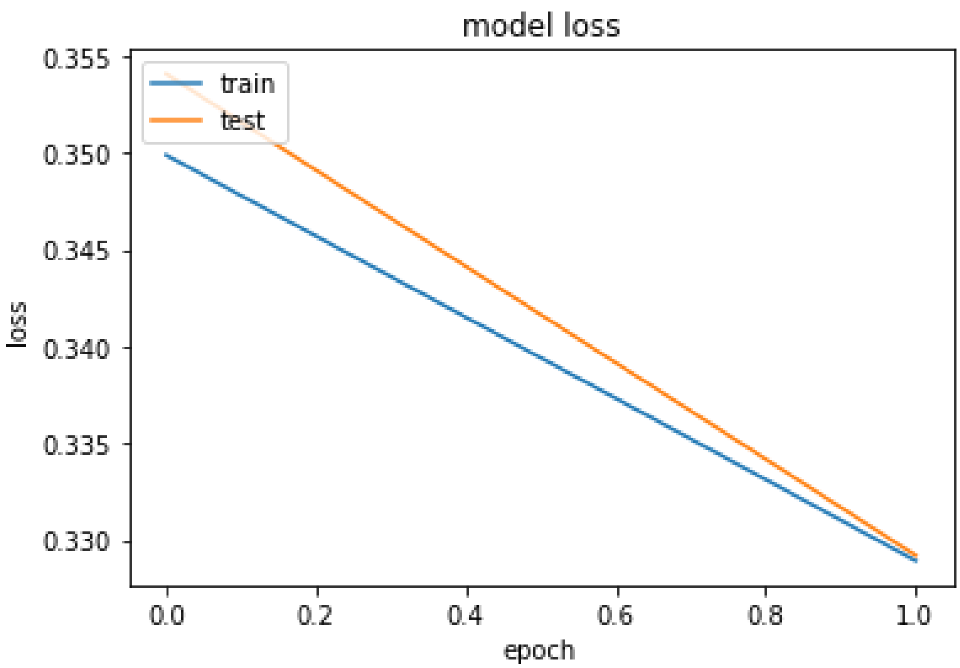
Our model

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 500, 100)          3377300

 conv1d (Conv1D)             (None, 496, 64)           32064

 max_pooling1d (MaxPooling1D  (None, 248, 64)          0
 )

 dropout (Dropout)           (None, 248, 64)           0

 lstm (LSTM)                 (None, 100)               66000

 dense (Dense)               (None, 50)                5050

 dense_1 (Dense)             (None, 4)                 204

=================================================================
Total params: 3,480,618
Trainable params: 103,318
Non-trainable params: 3,377,300
_________________________________________________________________
```

RESULTS

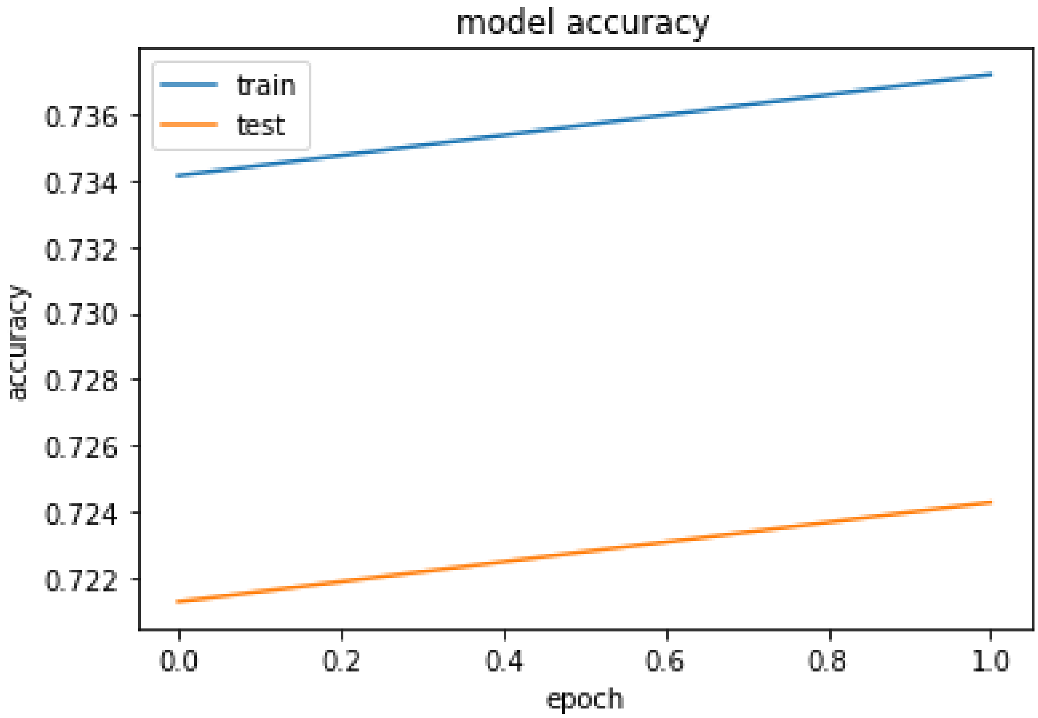
Without pre-processing

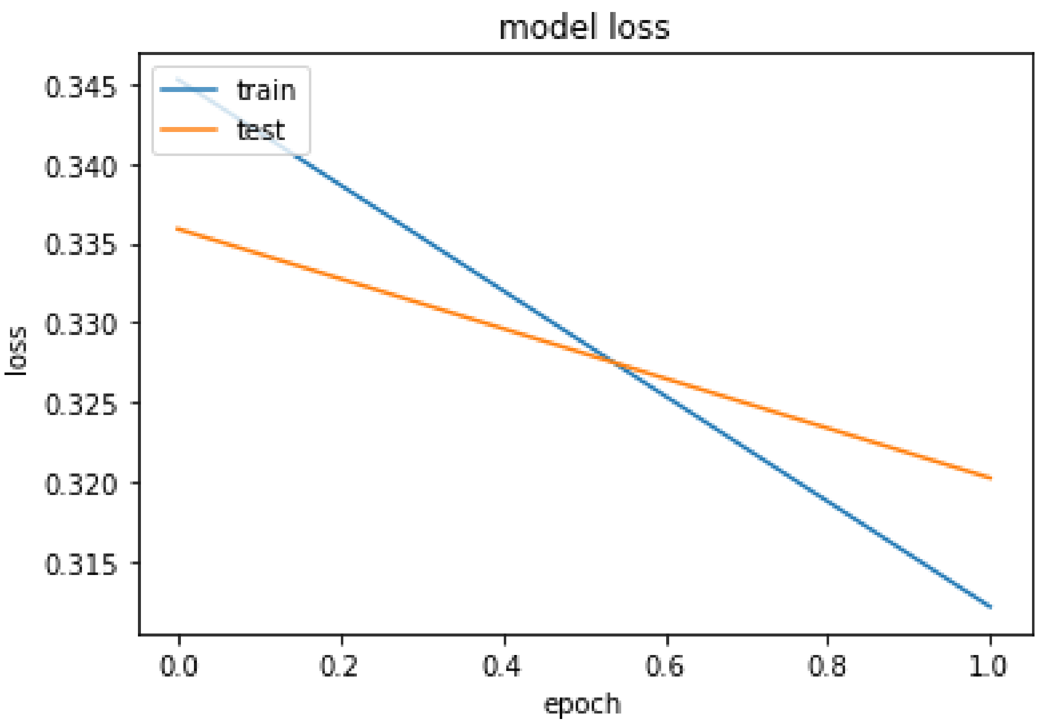





```
781/781 [==============================] - 56s 72ms/step - loss: 0.3107 - accuracy: 0.7390
Accuracy Train: 73.89737963676453
398/398 [==============================] - 28s 72ms/step - loss: 0.3573 - accuracy: 0.7267
Accuracy Test: 72.67432808876038
```

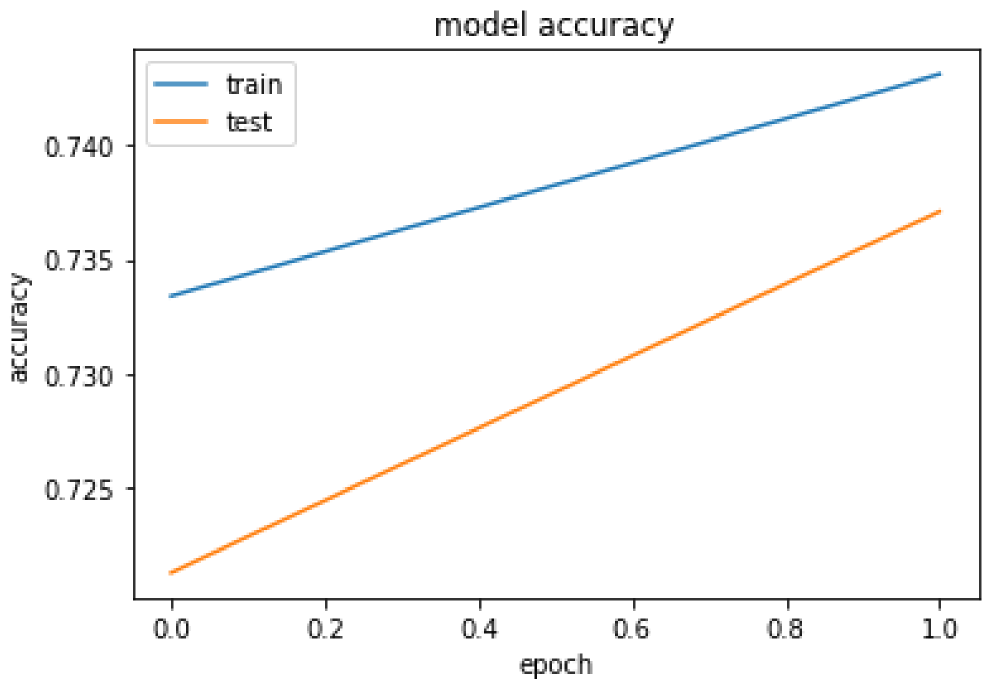
Without feature extraction

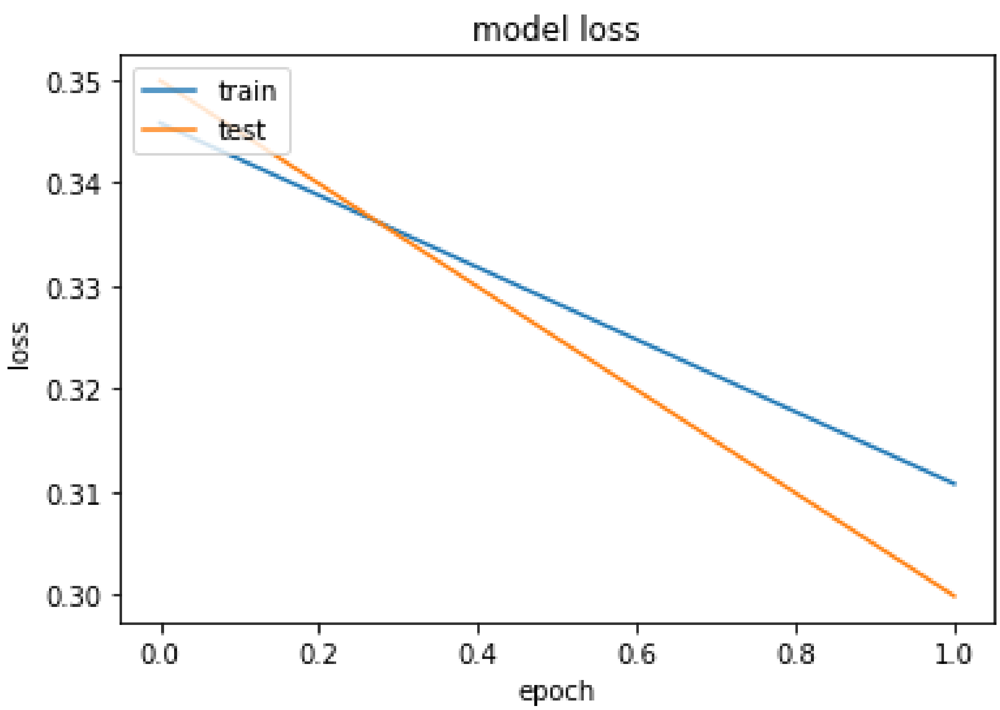





```
781/781 [==============================] - 56s 72ms/step - loss: 0.3047 - accuracy: 0.7416
Accuracy Train: 74.1575300693512
398/398 [==============================] - 29s 72ms/step - loss: 0.3478 - accuracy: 0.7320
Accuracy Test: 73.2016384601593
```

Chi-square model for feature extraction






```
781/781 [==============================] - 26s 33ms/step - loss: 0.2799 - accuracy: 0.7571
Accuracy Train: 75.71439743041992
398/398 [==============================] - 13s 33ms/step - loss: 0.3752 - accuracy: 0.7264
Accuracy Test: 72.64284491539001
```

Conclusion and future work

The accuracy we've been able to achieve is due to taking a lower percentage of the data as training data. As the paper reflects, the hybrid CNN LSTM is much more accurate in comparison to other models which were run by the authors. Going forward it seems to be a reliable model for Fake News Stance Detection.