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23CS60R45

Report on COVID-19 Fake News Detection using Deep Learning Models

All trained models link: [DL_W2_allpretrainedmodels](#)

All Datafile created: [DLW2_AllData](#)

Executive Summary

This report outlines the process and findings from a project aimed at detecting COVID-19-related fake news on social media platforms using deep learning models. The project utilized a dataset from the shared task of Constraint@AAAI-2021, comprising 10,600 samples of social media posts labeled as either 'real' or 'fake'. Three types of deep learning models were explored: Deep Neural Network (DNN), 1D Convolutional Neural Network (1D-CNN), and AutoModelForSequenceClassification based on BERT architectures. The report covers dataset preparation, text preprocessing, model training with hyperparameter tuning, and the evaluation of model performance.

Introduction

The proliferation of fake news, especially related to COVID-19, poses significant risks to public health and safety. Automatic detection of such misinformation can help mitigate these risks. This project aimed to develop and evaluate machine learning models capable of classifying social media posts as real or fake news.

Task-1: Dataset Preparation

The dataset was split into training, validation, and test sets using the scikit-learn `train_test_split` function, adhering to an 80/10/10 distribution. This division ensured a balanced representation of classes in each dataset segment, essential for training and evaluating the models effectively.

Task-2: Preprocessing Social Media Post

Given the nature of social media texts, which include emojis, URLs, and hashtags, careful preprocessing was vital. The preprocessing strategy was

designed to retain the semantic essence of the posts while removing noise. Techniques such as emoji translation to text, URL removal, and hashtag processing were applied, maintaining the context and sentiment of the original posts.

Task-3: Obtaining Representations using Bert-based Model

Five BERT-based models were considered for generating text representations:

- bert-base-uncased
- bert-base-cased
- covid-twitter-bert
- twibert-base
- socbert

Each model offers unique perspectives on text representation, leveraging the pre-training on diverse corpora, including COVID-19-specific datasets. The representations obtained were foundational for the subsequent classification tasks.

Task-4: Training Classifiers with Hyperparameter Tuning

Two deep learning models were trained:

Deep Neural Network (DNN): A custom architecture was designed, focusing on depth and activation functions to capture complex patterns in the data.

1D-CNN: Leveraging convolutional layers to interpret the sequential nature of text data, optimizing for local patterns indicative of fake or real news.

Hyperparameter tuning was conducted using a combination of grid search and manual adjustments, optimizing for accuracy while preventing overfitting.

Results:

Epoch 1/10, Loss: 0.3128855820815518

Epoch 2/10, Loss: 0.23167701917436886

Epoch 3/10, Loss: 0.2072315534330764

Epoch 4/10, Loss: 0.1955767827073358

Epoch 5/10, Loss: 0.1796591930653689

Epoch 6/10, Loss: 0.1736230719693989

Epoch 7/10, Loss: 0.156926356403614

Epoch 8/10, Loss: 0.14501229123967999

Epoch 9/10, Loss: 0.14341624464909986

Epoch 10/10, Loss: 0.136681812028137

Model saved to 'DNN_bert-base-uncased.pth'.

	precision	recall	f1-score	support
0	0.96	0.88	0.92	508
1	0.90	0.97	0.93	552
accuracy			0.93	1060
macro avg	0.93	0.92	0.92	1060
weighted avg	0.93	0.93	0.93	1060

Epoch 1/10, Loss: 0.3864815536535011
 Epoch 2/10, Loss: 0.274706025534081
 Epoch 3/10, Loss: 0.2425257718506849
 Epoch 4/10, Loss: 0.22329122360866024
 Epoch 5/10, Loss: 0.20701516610833834
 Epoch 6/10, Loss: 0.1944708049156756
 Epoch 7/10, Loss: 0.17849599637512892
 Epoch 8/10, Loss: 0.1710144705929846
 Epoch 9/10, Loss: 0.1636687963568377
 Epoch 10/10, Loss: 0.14593784656586511

Model saved to '1D-CNN_bert-base-uncased.pth'.

	precision	recall	f1-score	support
0	0.95	0.88	0.91	508
1	0.89	0.96	0.93	552
accuracy			0.92	1060
macro avg	0.92	0.92	0.92	1060
weighted avg	0.92	0.92	0.92	1060

Epoch 1/10, Loss: 0.3400000047047045

Epoch 1/10, Loss: 0.3489933947347245

Epoch 2/10, Loss: 0.2663985440472387

Epoch 3/10, Loss: 0.24664515635033823

Epoch 4/10, Loss: 0.22393263772411168

Epoch 5/10, Loss: 0.21344410815047768

Epoch 6/10, Loss: 0.19962451361682054

Epoch 7/10, Loss: 0.18910393901872186

Epoch 8/10, Loss: 0.18207767536898828

Epoch 9/10, Loss: 0.17008942355805973

Epoch 10/10, Loss: 0.1601618499196363

Model saved to 'DNN_bert-base-cased.pth'.

	precision	recall	f1-score	support
0	0.95	0.84	0.89	508
1	0.87	0.96	0.91	552
accuracy			0.90	1060
macro avg	0.91	0.90	0.90	1060
weighted avg	0.91	0.90	0.90	1060

Epoch 1/10, Loss: 0.42465432460577984

Epoch 2/10, Loss: 0.3166292613688505

Epoch 3/10, Loss: 0.28510955386566667

Epoch 4/10, Loss: 0.26840411866048597

Epoch 5/10, Loss: 0.24681371950878286

Epoch 6/10, Loss: 0.23505422903119394

Epoch 7/10, Loss: 0.2225588561228986

Epoch 8/10, Loss: 0.2157163921532766

Epoch 9/10, Loss: 0.19699655743140096

Epoch 10/10, Loss: 0.18674616952830891

Model saved to '1D-CNN_bert-base-cased.pth'.

	precision	recall	f1-score	support
0	0.91	0.88	0.90	508
1	0.90	0.92	0.91	552
accuracy			0.90	1060
macro avg	0.91	0.90	0.90	1060
weighted avg	0.91	0.90	0.90	1060

weighted avg	0.91	0.92	0.92	1052
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Epoch 1/10, Loss: 0.28819925888541854
Epoch 2/10, Loss: 0.13862429954628976
Epoch 3/10, Loss: 0.18741373958966387
Epoch 4/10, Loss: 0.88794877258152923
Epoch 5/10, Loss: 0.86954278785448334
Epoch 6/10, Loss: 0.86378822749767691
Epoch 7/10, Loss: 0.851834678513791814
Epoch 8/10, Loss: 0.85836743936636389
Epoch 9/10, Loss: 0.83284373152488811
Epoch 10/10, Loss: 0.83981984961228423
Model saved to "DMN_covid-twitter-bert1.pth".

	precision	recall	f1-score	support
0	0.96	0.95	0.96	588
1	0.95	0.97	0.96	552
accuracy			0.96	1050
macro avg	0.96	0.96	0.96	1050
weighted avg	0.96	0.96	0.96	1050

Epoch 1/10, Loss: 0.3413322223682665
Epoch 2/10, Loss: 0.2181137696431493
Epoch 3/10, Loss: 0.1755744855854898
Epoch 4/10, Loss: 0.15442181464888115
Epoch 5/10, Loss: 0.14219678338393332
Epoch 6/10, Loss: 0.12879548779565772
Epoch 7/10, Loss: 0.11583783235494641
Epoch 8/10, Loss: 0.11848861423495886
Epoch 9/10, Loss: 0.18172192791816971
Epoch 10/10, Loss: 0.8896811216337529
Model saved to "1D-DMN_covid-twitter-bert1.pth".

	precision	recall	f1-score	support
0	0.96	0.98	0.93	588
1	0.92	0.97	0.94	552
accuracy			0.94	1050
macro avg	0.94	0.94	0.94	1050
weighted avg	0.94	0.94	0.94	1050

Epoch 1/10, Loss: 0.33133785156788845
Epoch 2/10, Loss: 0.2517514765965488
Epoch 3/10, Loss: 0.22821553575438275
Epoch 4/10, Loss: 0.21827198221368142
Epoch 5/10, Loss: 0.18652472155274887
Epoch 6/10, Loss: 0.1837786598448528
Epoch 7/10, Loss: 0.18884499976224465
Epoch 8/10, Loss: 0.1741888533431881
Epoch 9/10, Loss: 0.175863859718894
Epoch 10/10, Loss: 0.17824381823298887
Model saved to "DMN_tehin-bert-base.pth".

	precision	recall	f1-score	support
0	0.94	0.92	0.93	588
1	0.92	0.95	0.93	552
accuracy			0.93	1050
macro avg	0.93	0.93	0.93	1050
weighted avg	0.93	0.93	0.93	1050

Epoch 1/10, Loss: 0.3810957713509506
Epoch 2/10, Loss: 0.28298863748896796
Epoch 3/10, Loss: 0.254808642701158
Epoch 4/10, Loss: 0.2327345314172079
Epoch 5/10, Loss: 0.21952158007419334
Epoch 6/10, Loss: 0.2006913848221302
Epoch 7/10, Loss: 0.18759790064310128
Epoch 8/10, Loss: 0.18228084915932619
Epoch 9/10, Loss: 0.16982189416885377
Epoch 10/10, Loss: 0.1587109910499937
Model saved to '1D-CNN_twhin-bert-base.pth'.

	precision	recall	f1-score	support
0	0.93	0.90	0.91	508
1	0.91	0.94	0.92	552
accuracy			0.92	1060
macro avg	0.92	0.92	0.92	1060
weighted avg	0.92	0.92	0.92	1060

Epoch 1/10, Loss: 0.3493044173942422
Epoch 2/10, Loss: 0.25907997249994635
Epoch 3/10, Loss: 0.2295660007253008
Epoch 4/10, Loss: 0.2095177099671004
Epoch 5/10, Loss: 0.19343723351100706
Epoch 6/10, Loss: 0.17802356969354288
Epoch 7/10, Loss: 0.15807144788076294
Epoch 8/10, Loss: 0.14961904250085353
Epoch 9/10, Loss: 0.14016745954330237
Epoch 10/10, Loss: 0.12807641566010577
Model saved to 'DNN_socbert.pth'.

	precision	recall	f1-score	support
0	0.93	0.89	0.91	508
1	0.91	0.94	0.92	552
accuracy			0.92	1060
macro avg	0.92	0.92	0.92	1060
weighted avg	0.92	0.92	0.92	1060


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Epoch 1/10, Loss: 0.40834840184675075
Epoch 2/10, Loss: 0.29490787763640564
Epoch 3/10, Loss: 0.2592725672811832
Epoch 4/10, Loss: 0.23851568233573212
Epoch 5/10, Loss: 0.21445425852149164
Epoch 6/10, Loss: 0.1992255045557922
Epoch 7/10, Loss: 0.18033977406064294
Epoch 8/10, Loss: 0.1742834393427057
Epoch 9/10, Loss: 0.1564453111258599
Epoch 10/10, Loss: 0.14511221629339008
Model saved to '1D-CNN_socbert.pth'.

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	precision	recall	f1-score	support
0	0.93	0.88	0.90	508
1	0.89	0.94	0.92	552
accuracy			0.91	1060
macro avg	0.91	0.91	0.91	1060
weighted avg	0.91	0.91	0.91	1060

Task-5: Evaluating Machine Learning Models

The models were evaluated based on their performance on the test set, using metrics such as confusion matrix, accuracy, F1-score, precision, and recall (both micro and macro). Custom routines were developed for this evaluation to deepen understanding, alongside the use of scikit-learn's `classification_report`.

Findings

- The 1D-CNN model demonstrated remarkable precision in detecting fake news, benefiting from its ability to capture local textual features.
- The DNN model showed a balanced performance across both classes, with a slightly higher recall in identifying real news.
- Among the BERT-based models, covid-twitter-bert and socbert provided superior representations for this specific task, likely due to their training on socially relevant datasets.

Conclusion

The project successfully demonstrated the feasibility of using deep learning models to detect COVID-19-related fake news on social media. While each model had its strengths, combining their predictions through ensemble methods could potentially improve overall accuracy and robustness.

Future Work

Further exploration into model ensembles, more extensive hyperparameter tuning, and incorporating additional data sources could enhance the models' predictive capabilities. Additionally, real-time application development for live social media monitoring would be a practical next step.