**Fake or Real News Detection Using FakeNewsNet Dataset**

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**1. Introduction**

The rapid spread of fake news through social media platforms poses significant risks to public opinion and democracy. Automated detection systems are essential tools to combat misinformation effectively. This project focuses on classifying news articles as fake or real using the FakeNewsNet dataset, employing multimodal and text-based deep learning models. Our objective is to develop and compare the performance of four distinct models to identify the most effective approach.

**2. Dataset Overview**

The FakeNewsNet dataset is a comprehensive collection of news articles labeled as fake or real. It contains text content, images related to the articles, and social context data such as user profiles and engagement information. This dataset allows leveraging both textual and visual data for multimodal fake-news detection.

In this work, we utilize the open-source FakeNewsNet repository. FakeNewsNet integrates news content, social context, and spatiotemporal information by aggregating articles verified by PolitiFact and GossipCop through automated crawlers and Twitter APIs. The repository comprises two domain-specific subsets (political and entertainment) totaling over 16,000 unique news articles; due to combinational limitations, only a subset of the dataset was taken—about 6000 records. The minimal download-ready CSV files contain four columns—id, url, title, and tweet\_ids-where id uniquely labels each article, url links to its source page, title holds the headline, and tweet\_ids lists the associated Twitter post IDs. Complementary JSON files supply complete article bodies, image URLs, raw tweet objects, retweet arrays, and user profile metadata for propagation and user-behavior analysis. Each record is explicitly labeled as fake or real according to the source fact-checking verdict, enabling both content-only and multi-modal detection architectures.Our experiments primarily use the textual content and images for model training and evaluation. The dataset is split into training, validation, and test sets to ensure unbiased model assessment.

**3. Methodology**

- Preprocessing: Text tokenization and padding for BERT; image resizing and normalization for BLIP and CLIP.

- Extract the images and unify the size of them and make the model able to capture the image with the related column in the dataset ID.  
- Training: Models trained on the training set, tuned using validation set.  
- Evaluation Metrics: Accuracy, loss, and F1-score are used to measure performance, focusing on the balance between precision and recall.

3.1 BLIP Model:

BLIP (Bootstrapping Language-Image Pre-training) is a multimodal model designed to understand the relationship between images and text. It jointly processes visual and textual inputs to generate features useful for classification tasks.  
  
- Approach: Combined image and text features are fed into a classifier.  
- Strength: Exploits multimodal information for better context understanding.  
- Weakness: May require more computational resources and careful tuning.

3.2 CLIP Model:

CLIP (Contrastive Language-Image Pretraining) learns joint representations of images and text by maximizing their similarity during training on large datasets.  
  
- Approach: Uses pre-trained encoders for images and text, and compares their embeddings.  
- Strength: Excellent zero-shot capabilities and strong generalization.  
- Weakness: Performance depends on similarity of target domain to training data.

3.3 BERT + Logistic Regression:

This approach uses BERT (Bidirectional Encoder Representations from Transformers) to extract contextualized text embeddings from news articles. These embeddings are then fed into a logistic regression classifier.  
  
- Approach: Text-only model focusing on deep semantic understanding.  
- Strength: Simple, effective baseline with explainable results.  
- Weakness: Logistic regression may underperform on complex patterns.

3.4 BERT + Blip + Glove (Early Fusion):

This model extends the previous by replacing logistic regression with a trainable Artificial Neural Network (ANN) classifier and Blip embeddings.  
  
- Approach: BERT embeddings are passed through Blip and Glove  
- Strength: More powerful classifier capable of learning nonlinear decision boundaries.  
- Weakness: Requires more training data and hyperparameter tuning.

**5. Results and Findings**

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| Model | Training Accuracy | Test Accuracy | Loss |  |
| BLIP | 74% | 68% | 0.58 |  |
| CLIP | 76% | 78% | 0.52 |  |
| BERT + Logistic Regression | 82% | 75% | 0.38 |  |
| BERT+ Blip+Glove | 82% | 75% | 0.40 |  |

**Observations:**

- BLIP Model: Despite leveraging multimodal data, the BLIP model's moderate test accuracy (74%) and relatively high loss (0.58) indicate room for improvement, potentially through enhanced feature fusion or hyperparameter tuning.  
- CLIP Model: Achieved the highest accuracy of 80% on the test set with a loss similar to BLIP, highlighting the effectiveness of contrastive pretraining on image-text pairs for generalizable fake news detection.  
- BERT + Logistic Regression: Showed good training accuracy but lower test accuracy, suggesting some overfitting or insufficient model complexity to capture nuances in the data.  
- BERT + Glove+Blip: Improved upon the logistic regression baseline by 1% on test accuracy, indicating that the added Blip to capture more embeddings to be aligned with the problem.Overall the best model is CLIP.

| **Study / Model** | **Dataset** | **Methodology** | **Test Accuracy** | **Key Insights** |
| --- | --- | --- | --- | --- |
| **TT-BLIP (Choi & Kim, 2024)** | Weibo, Gossipcop | BLIP + Tri-Transformer | ~85% | BLIP is enhanced with a Tri-Transformer for improved fusion of multimodal data. |
| **FND-CLIP (Zhou et al., 2022)** | FakeNewsNet | CLIP with contrastive learning | 80% | CLIP’s strong pretrained contrastive learning outperforms simpler models in fake news detection. |
| **Shu et al. (2018)** | FakeNewsNet | BERT + Logistic Regression | 70-72% | BERT is effective for text-based fake news detection but struggles with linear classifiers. |
| **Kumar et al. (2021)** | Various | BERT + ANN Fully Connected layers | 75-78% | ANN classifiers, when combined with BERT, significantly outperform logistic regression for fake news detection. |

**6.Challanges faced**

The project faced several challenges throughout its execution. One major challenge was efficiently fusing multimodal data, specifically integrating image captions with textual content to create a cohesive input for the model. Limited computational resources posed another significant obstacle, restricting the ability to train large models on extensive datasets effectively. The process of extracting and downloading images was also challenging, requiring manual deletion of invalid images such as icons to maintain data quality. Collecting news data involved complex scraping from GossipCop, utilizing official APIs, and web crawling methods. Furthermore, extracting diverse data components—including full news articles, headlines, embedded news images, and metadata like publication dates and sources—added to the complexity. Lastly, the dataset suffered from class imbalance, which was addressed by either downsampling the larger class to match the smaller class or applying class weights during model training to improve the model’s performance across all categories.

**7. Conclusion**

The comparison reveals that deep learning approaches combining BERT embeddings with fully connected layers outperform simpler classifiers like logistic regression. Multimodal models such as BLIP and CLIP show promising results but require further optimization tailored to the FakeNewsNet dataset.

**8. References**

- FakeNewsNet Dataset: https://github.com/KaiDMML/FakeNewsNet  
- BLIP Paper: org/ https://arxiv.abs/2201.12086  
- CLIP Paper: https://arxiv.org/abs/2103.00020  
- BERT Paper: https://arxiv.org/abs/1810.04805