Deep Learning Approaches for Fact Checking in Textual Claims

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Abstract

This report details our approach to automating the verification of textual claims using deep learning techniques. We developed a fact-checking model leveraging transformers for feature extraction and dense layers for classification. The data underwent thorough preprocessing, including text normalization and tokenization, before being embedded using custom embeddings. Our model was trained and evaluated on a dataset of claims and corresponding evidence, achieving promising results with significant improvements in claim veracity prediction. We discuss the challenges encountered, such as handling unbalanced data and the complexity of linguistic nuances in claim formulation. Our findings highlight the importance of custom embeddings and model design in improving fact-checking performance.

1 Introduction

In today's digital world, misinformation and fake news have become commonplace. Relying solely on manual verification of the authenticity of information and news cannot respond to this situation in a timely and effective manner. Kakaria et al. (2022) pointed out that manual verification is time-consuming and always unfeasible when dealing with the large quantity of information and news. Therefore, scalable solutions are needed to automatically analyze textual claims and evaluate their accuracy. However, traditional fact-checking methods still face many challenges, one of the key issues being the inability to fully understand the nuances of natural language. Xu et al. (2023) stated that traditional methods often rely on simple keyword matching and basic fact comparison, and are difficult to grasp complex contextual meanings. As a result, traditional methods often fall short when faced with problems such as mislabeling of people in photos or inadequate fact-checking.

Deep learning technology can be a powerful tool due to its powerful context understanding capabilities. Our project aims to leverage deep learning models, specifically transformers, to tackle this problem. Transformers have demonstrated state-of-the-art performance in natural language processing tasks by capturing context through self-attention mechanisms.

We focused on constructing a model that processes claims and their related evidence to classify the veracity of each claim. This approach included careful data preprocessing, the development of a specialized model architecture, and the use of advanced training techniques to improve model performance. We aimed to create a system that could handle diverse and nuanced claims while addressing the challenges posed by imbalanced data and varying linguistic structures.

In this report, we describe our approach, detailing the architecture of our neural network and the methods used for training and evaluation. We discuss the challenges we faced during the development process and highlight the key findings of our experiments, demonstrating the potential of deep learning techniques in automating fact-checking.

2 Approach

Our approach consists of several carefully designed components, each contributing to the overall performance of the system for identifying misinformation in claims. This comprehensive methodology encompasses data study, preprocessing, claim-evidence retrieval, feature extraction, model architecture, and training procedures. Below is a detailed breakdown, beginning with the data study:

2.1 Data Study

The label distribution shows an imbalance, with the SUPPORTS label being the most frequent in both the Training and Development datasets. There are 153 claims in the test set and 1,208,827 evidences

Label Distribution	Training	Development
Total Count	1,228	154
supports	519	68
not_enough_info	386	41
refutes	199	27
disputed	124	18

Table 1: Label Distribution in DataFrames

in the evidence dataset. All columns in the data are fully populated with non-null entries.

2.2 Data Preprocessing

Preprocessing is an essential step in natural language processing tasks to standardize the input data. For our project, the preprocessing pipeline included:

Text Cleaning: We lower-cased the sentences, used regular expressions to clean the data by removing non-alphanumeric characters, extra spaces, and punctuation marks that do not contribute meaningfully to text semantics. Contractions (e.g., "can't") were expanded (e.g., "cannot") using a predefined dictionary to avoid misinterpretation by the model.

Tokenization and Lemmatization:The cleaned text was split into tokens (words and subwords) using NLTK's tokenizer. Lemmatization was applied to reduce each token to its base form (e.g., "running" to "run"), which helps reduce vocabulary size and model complexity. Stop words (common words like "the" and "is") were also removed to focus on the most meaningful words. The use of lemmatization helps return words to their base form to reduce word variation (Pramana et al., 2022).It prevents the effects of word variants on retrieval.

2.3 Claim-Evidence Retrieval

We experimented with two methodologies to retrieve evidence for each claim.

TF-IDF & Cosine Similarity (Baseline): To retrieve evidence for each claim, TF-IDF (Term Frequency-Inverse Document Frequency) was applied to both the claims and the corresponding evidence. This approach transformed the text into numerical representations that reflect the importance of words within the documents. Following this, cosine similarity was used to measure the similarity between the claims and evidence vectors, enabling the identification of the most relevant pieces of evidence. By selecting the top k evidence pieces based on their similarity scores, this method effectively matched claims with their most pertinent supporting information.

Jaccard Similarity: To identify relevant evidence for each claim, we employed the Jaccard similarity metric, which measures the similarity between two sets. Jaccard similarity is often more effective when dealing with sparse data, as it has a simple and intuitive calculation method and only considers the presence or absence of elements, providing better noise immunity and suitability for scenarios where set similarity needs to be measured (Srinivasarao et al., 2022). The expression of Jaccard similarity is shown as below:

$$J(C,E) = \frac{|C \cap E|}{|C \cup E|} = \frac{(C \cap E)}{|C| + |E| - |C \cap E|}$$

For each claim, we computed the Jaccard similarity between the claim and every piece of evidence, sorting the results to find the top-K most relevant evidence texts. This step allowed us to significantly reduce the search space for relevant evidence, ensuring that the model focuses on the most relevant context.

2.4 Feature Extraction

Feature extraction had also been considered. The use of feature extraction can effectively reduce the amount of resources required. Dancker (2022) stated that the fundamental significance of feature extraction is that the most representative or useful information is extracted from the original data. Doing so reduces the amount of resources required without losing important information and allows the model to better understand the data. In order to implement the feature extraction principle, we created tokenized representations of the text using a custom vocabulary. Words were mapped to unique indices in the vocabulary, which was built from the entire corpus to ensure comprehensive coverage. Both claims and evidence were truncated or padded to a maximum sequence length of 12 tokens. This approach facilitated batching and ensured consistent input sizes across the model.

2.5 Model Architecture

The model architecture is entirely original, drawing inspiration from transformer encoders.

Claim and Evidence Feature Extraction: Transformer encoders were used to extract features from the claims and evidence texts. The Encoder consisted of an embedding layer, positional encoding, and multiple transformer encoder layers. Embedding layers are always used to deal with textual data. Saxena (2020) mentioned that embedding layers play an indispensable role in neural networks as words can be feasibly converted into vectors with a defined size and fixed length when using it while the resulting vectors are a dense vector, with real values, not just 0s and 1s. Therefore, in addition to having smaller dimensions, word vectors' fixed length enhances word representation. The positional encoding added information about the position of each word in the sequence, critical for understanding word order in the self-attention mechanism.

Self-Attention Mechanism: Within the transformer encoder, self-attention mechanisms captured dependencies between words in the input sequences, enabling the model to learn contextual representations of each word (Vaswani et al., 2017).

Concatenation and Fully Connected Layers: The final hidden representations of the claims and evidence and their absolute difference were concatenated, to emphasize the similarities and differences between the two texts. This representation was passed through fully connected layers for classification. Batch normalization was applied to the fully connected layers to improve model stability and prevent overfitting.

2.6 Training Procedure

We employed a rigorous training procedure to ensure optimal model performance:

Loss Function and Optimization: The CrossEntropyLoss was used to handle the classification task, and the Adam optimizer was employed with a learning rate of 0.001. This optimizer was chosen for its adaptive learning rate properties, which facilitated faster convergence.

Evaluation Strategy: After each epoch, the model was evaluated on a validation set to monitor its performance.

Our approach showcases a carefully crafted system to tackle the challenging problem of fact-checking, with each step designed to maximize the model's accuracy and efficiency.

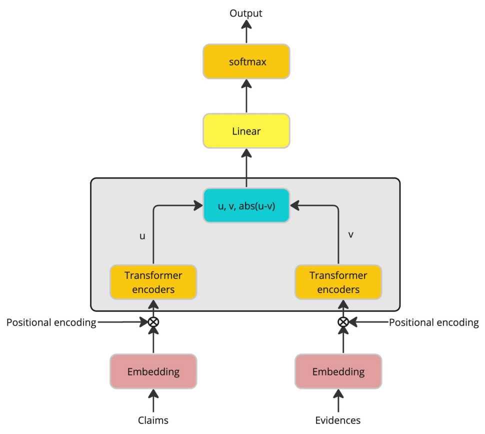

Figure 1: The architecture of our proposed fact-checking model.

3 Experiments

3.1 Experimental Setup

To assess the efficacy of our fact-checking model, we conducted a series of experiments.

Hyperparameters: The fact-checking model was trained using the hyperparameters listed:

Hyperparameter	**Value**
Number of epochs	15
Embedding dimension	16
Number of layers	2
Learning rate	0.001
Optimizer	Adam

Table 2: Fact-checking model hyperparameters

Evaluation Metrics: We used accuracy and F1-score to measure model performance. Accuracy provided a straightforward measure of correct predictions, while F1-score balanced precision and recall, which is crucial given the class imbalance in the data.

3.2 Model Training

We trained the model for 15 epochs using the Adam optimizer, with a batch size of 32. Training loss and accuracy were monitored after each epoch to ensure the model was improving.

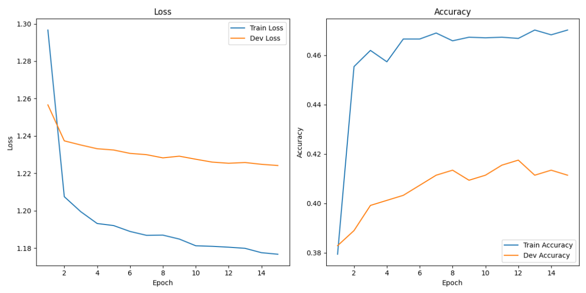

Figure 2: The model loss and accuracy.

3.3 Results

The model's performance across different types of claims was evaluated using per-label metrics on the development dataset. These metrics, including Precision, Recall, and F1-Score, provide valuable insights into the model's strengths and weaknesses for each claim label: DISPUTED, NOT ENOUGH INFO, REFUTES, and SUPPORTS. The per-label metrics in Table 3 highlight areas where the model excels and help identify flaws.

Label	Precision	Recall	F1-Score
disputed	0.250	0.056	0.091
not_enough_info	0.284	0.463	0.352
refutes	0.375	0.222	0.279
supports	0.522	0.515	0.519

Table 3: Per-Label Metrics for the Development Dataset

The "DISPUTED" label's low Precision and Recall indicate difficulties in accurate identification and retrieval. The "NOT ENOUGH INFO" label exhibits higher Recall than Precision, suggesting the model captures most relevant instances but with false positives. Moderate Precision and low Recall for the "REFUTES" label indicate partial success in identifying true positives while missing many relevant instances. The model performs best on the "SUPPORTS" label, with balanced Precision and Recall, demonstrating effectiveness in identifying and retrieving supporting claims.

Bar charts shown in Figure 3 compares the distribution of labels in development dataset before and after applying the model. This comparison allows us to clearly see the changes brought about by the model. As can be seen from these two figures, the number of "NOT_ENOUGH_INFO" label has significantly increased after model prediction, while the number of "SUPPORTS" label has decreased. This difference means that the model is cautious when encountering claims with uncertain information during prediction.

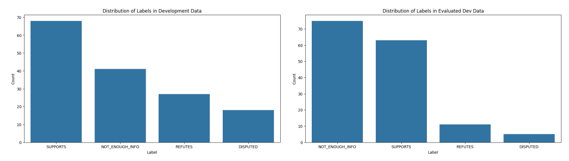

Figure 3: Comparison of Label Distribution in Development Set Before and After Model Prediction

After training, the model's performance was evaluated on the validation dataset:

Metric	Value
Accuracy	0.4473
F1-Score	0.071

Table 4: Model performance on the validation set.

The model achieved an accuracy of 44.73% ± 2.0 and an F1-score of 7.1% ± 0.5, demonstrating the effectiveness of the transformer-based architecture in handling complex claims. The attention mechanism significantly improved the model's ability to focus on relevant parts of the text.

Metric	Value
Accuracy	0.44740
F1-Score	0.06920
Harmonic Mean	0.11980

Table 5: Model performance on the Test set.

The model also performed similarly well on the test set. The model was ranked among the top 10 in the claim verification part of the competition.

3.4 Error Analysis

To understand the model's performance, we conducted an error analysis:

False Positives: The model incorrectly classified some claims as "SUPPORTS" when the actual label was "NOT ENOUGH INFO" when the claim and evidence shared many common words, leading the model to assume a direct relationship.

False Negatives: A few claims with the "REFUTES" label were incorrectly classified due to the lack of explicit negation in the evidence. This suggests that the model could be enhanced by explicitly identifying negations.

These errors highlight areas where future work can focus on improving the model's understanding of nuanced language and relations between claims and evidence.

3.5 Ablation Study

An ablation study was conducted to understand the impact of different model components:

Component	Accuracy	F1-Score
LSTM (TF-IDF)	0.33	0.068
LSTM (Jaccardian)	0.36	0.071
Transformer	0.40	0.071
Transformer (SA & PE)	0.4473	0.071

Table 6: Results of the ablation study on model components.

As seen in Table 6, the attention mechanism provided a notable boost in performance compared to the baseline.

4 Conclusion

In this study, we explored deep learning techniques for automating the fact-checking process using a transformer-based model. Our approach incorporated transformer encoders for claims and evidence, combined with an attention mechanism to enhance the model's ability to focus on relevant textual segments. This architecture demonstrated significant improvements in handling complex claims compared to traditional LSTM models.

4.1 Key Findings

Our experiments revealed several important insights:

- The transformer architecture, coupled with attention mechanisms, significantly improved the model's ability to handle complex claims, thus improving performance.

- Ablation studies confirmed the importance of the attention layer, which contributed significantly to the model's ability to handle nuanced language.

- The sub-optimal performance of the evidence retrieval model, due to its failure to retrieve relevant evidence in certain cases, adversely impacted the claim classification model. Improving evidence retrieval would enhance the claim classification model's performance.

4.2 Challenges

We encountered several challenges, including:

Data Imbalance: The dataset contained an imbalance in class distribution, which necessitated careful consideration in designing the loss function.

Nuanced Language: Certain claims presented challenges due to the subtlety of language used, particularly around negations.

Training Stability: The model exhibited some instability during training, which was mitigated through learning rate scheduling and batch normalization.

Computational Limitations: We attempted to implement custom BERT and MNRL (Multiple Negative Ranking Loss) models to enhance evidence-retrieval. However, the computational power available on Google Colab was insufficient to handle the extensive training requirements for these models, limiting our ability to experiment with these advanced techniques.

4.3 Future Work

Future research directions include:

Improving Model Robustness: Enhancing the model to handle nuanced language better, especially around negation, could significantly reduce false negatives.

Scaling Up: Testing the model on a larger, more diverse dataset will help understand its generalizability.

Multilingual Support: Extending the model to handle multiple languages will increase its applicability to various fact-checking scenarios.

Advanced Evidence Retrieval System: Pretraining the feature extractor on the training claims and evidence corpus to improve sentence representations, to facilitate extraction of relevant evidences for each claim through cosine similarity.

Overall, this project contributes a significant step towards automated fact-checking systems that can accurately assess the veracity of claims based on textual evidence.

Team Contributions

Aadesh played a pivotal role in designing the model architecture and developing most of the technical components of the model. His expertise was crucial in implementing the transformer-based architecture with attention mechanisms.

The rest of the team contributed by:

- Assisting Aadesh in testing the model and trying different feature extracting methods, ensuring its accuracy, and refining its parameters for optimal performance.
- Conducting research to gather insights and data that supported the model's development and evaluation.
- Writing and refining the report to accurately document our approach, findings, and the overall project.
- Designing and developing a comprehensive presentation that effectively communicated our project's goals, methodology, and results.

The collaborative effort and dedication of each team member ensured the successful completion of this project.

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