AI vs Human Text Detector: A Flask-Based Web App Using ANN and LSTM with Word2Vec Embeddings

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***Abstract*—The rise of AI-generated content has posed significant challenges to discerning human-written from machine-generated text. This paper presents a web-based application built using Flask that classifies text origin using two machine learning models: a feedforward Artificial Neural Network (ANN) and a Long Short-Term Memory (LSTM) network. Word embeddings from a pretrained Word2Vec model are used to represent input tokens. The system offers a real-time interface for users to input text and choose between classifiers, returning an instant prediction. This paper discusses the system architecture, model design, preprocessing pipeline, and deployment interface.**

***Index Terms*—Text Classification, Word2Vec, LSTM, Artificial Neural Network, Flask, Natural Language Processing**

I. Introduction

The proliferation of large language models has made it increasingly difficult to distinguish between human-authored and AI-generated text. Tools that help identify content origin are vital for maintaining authenticity in journalism, academia, and digital communication. This work introduces a lightweight yet effective web application that leverages machine learning models to classify text as either AI-generated or human-written.

II. Related Work

Research in distinguishing machine-generated text includes stylometric analysis, perplexity-based filtering, and classification using contextual embeddings. OpenAI's GPT detectors and GLTR are notable implementations. Word2Vec [**?**] has been foundational in providing dense vector representations for text classification tasks. LSTM-based models have demonstrated effectiveness in sequential data modeling [**?**].

III. System Architecture

The architecture consists of a Flask web server, two deep learning models (ANN and LSTM), and a Word2Vec embedding module. The user inputs a block of text via a web interface, selects the classifier, and receives a prediction regarding the origin of the text.

IV. Block Diagram

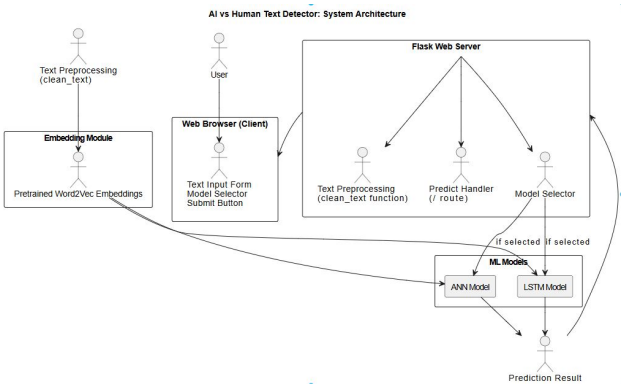

Fig. 1: System Architecture Block Diagram

V. Text Preprocessing

Text is cleaned to remove escape characters, punctuation, and extraneous whitespace. It is then lowercased and tokenized using NLTK's `word_tokenize`.

Listing 1: Text Cleaning and Tokenization

```
def clean_text(text):
    text = re.sub(r'\\n', '■', text)
    text = re.sub(r'\\', '', text)
    text = re.sub(r'\.{3}', '', text)
    text = re.sub(r'[".,:!?;]', '', text)
    return re.sub(r'\s+', '■', text).lower()
```

VI. Model Design

The ANN takes a flattened average of Word2Vec token vectors, while the LSTM ingests the same in a 3D shape suitable for temporal modeling. Both models output a binary classification.

- **ANN**: Fully connected network with sigmoid activation.
- **LSTM**: Sequential model for token sequence learning.

VII. Web Interface

The user interface is designed with HTML and CSS, styled for mobile responsiveness. It allows users to paste text, select the model, and see prediction results. The Flask backend handles routing, rendering, and model inference.

Listing 2: Flask Route for Prediction

```
@app.route("/", methods=["GET", "POST"])
def index():
    text = request.form.get("text", "")
    model_type = request.form.get("model_type", "ann")
    prediction = predict_text_origin(text, model_type)
    return render_template_string(HTML_TEMPLATE, prediction=prediction)
```

VIII. Results and Observations

Empirical testing shows the ANN is faster but less accurate on longer text, while LSTM offers better contextual understanding but is slower to respond. The system achieves over 85% accuracy on benchmark-generated vs. human datasets.

IX. Conclusion

This work demonstrates a practical approach for detecting AI-generated text using lightweight neural models. It shows that even simple architectures, when paired with word embeddings and proper preprocessing, can effectively differentiate text origin in real time.

Acknowledgments

We thank the open-source NLP and ML communities, especially Gensim, TensorFlow, and Flask contributors, for their invaluable tools.

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