INDIAN INSTITUTE OF INFORMATION TECHNOLOGY DESIGN & MANUFACTURING, Kancheepuram

B.Tech Computer Science and Engineering
CS3008 (Core) + CS5101 (Elective) - Deep Learning

Fake News Detection Using LSTM AND BERT

REPORT

CS22B1007 - Chaitanya
CS22B1008 - Srinath
CS22B2007 - Suchith

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1 Introduction

The proliferation of fake news in the digital era has become a significant concern, influencing public opinion and undermining trust in legitimate information sources. Traditional methods of detecting misinformation, such as manual fact-checking, are insufficient to keep pace with the rapid dissemination of content online. To address this challenge, researchers have turned to deep learning techniques, notably **Long Short-Term Memory** (LSTM) networks, for automated fake news detection. LSTM models are adept at capturing temporal dependencies in sequential data, making them suitable for analyzing the context and flow of language in news articles. By processing sequences of words, LSTM networks can identify patterns indicative of deceptive content, such as sensationalist language or inconsistent narratives. Studies have demonstrated the efficacy of LSTM-based models in distinguishing between genuine and fake news, highlighting their potential as tools for mitigating the spread of misinformation .

Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained language model that excels at understanding the context of words in a sentence by considering both preceding and succeeding words simultaneously. This bidirectional approach allows BERT to grasp nuanced meanings and detect subtle cues that may indicate falsehoods in news content. Fine-tuning BERT on specific fake news datasets enables the model to adapt to the unique linguistic patterns associated with misinformation. Research has shown that BERT-based models outperform traditional machine learning algorithms and earlier deep learning approaches in accuracy and reliability, making them a powerful asset in the fight against fake news .

2 Dataset

- **Dataset Used:** ISOT Fake News Dataset
- **Classes:** Fake (1), Real (0)
- **Total Samples:** 45,000
  - Fake: 23,500
  - Real: 22,500

3 LSTM-Based Approach

3.1 Data Preprocessing

- Lowercasing
- Removal of URLs and stopwords
- Lemmatization
- Tokenization using TensorFlow
- Padding sequences to length 300
- **Example:**

```
Example of tokenized sequence:
Original text: st century wire say ben stein reputable professor ...
Tokenized sequence: [488, 603, 504, 20, 1646, 2826, 1, 1214, 1, 336, 12, 1289, 6129, 3566, 868]...
Training set: (35345, 300), Test set: (8837, 300)
```

Figure 1: Tokenization of Sequence

3.2 Model Architecture

- Embedding Layer (input_dim = 10,000)
- Dropout Layer
- LSTM Layer with 100 units
- Dense output layer with sigmoid activation
- Optimizer: Adam
- Loss: Binary Crossentropy

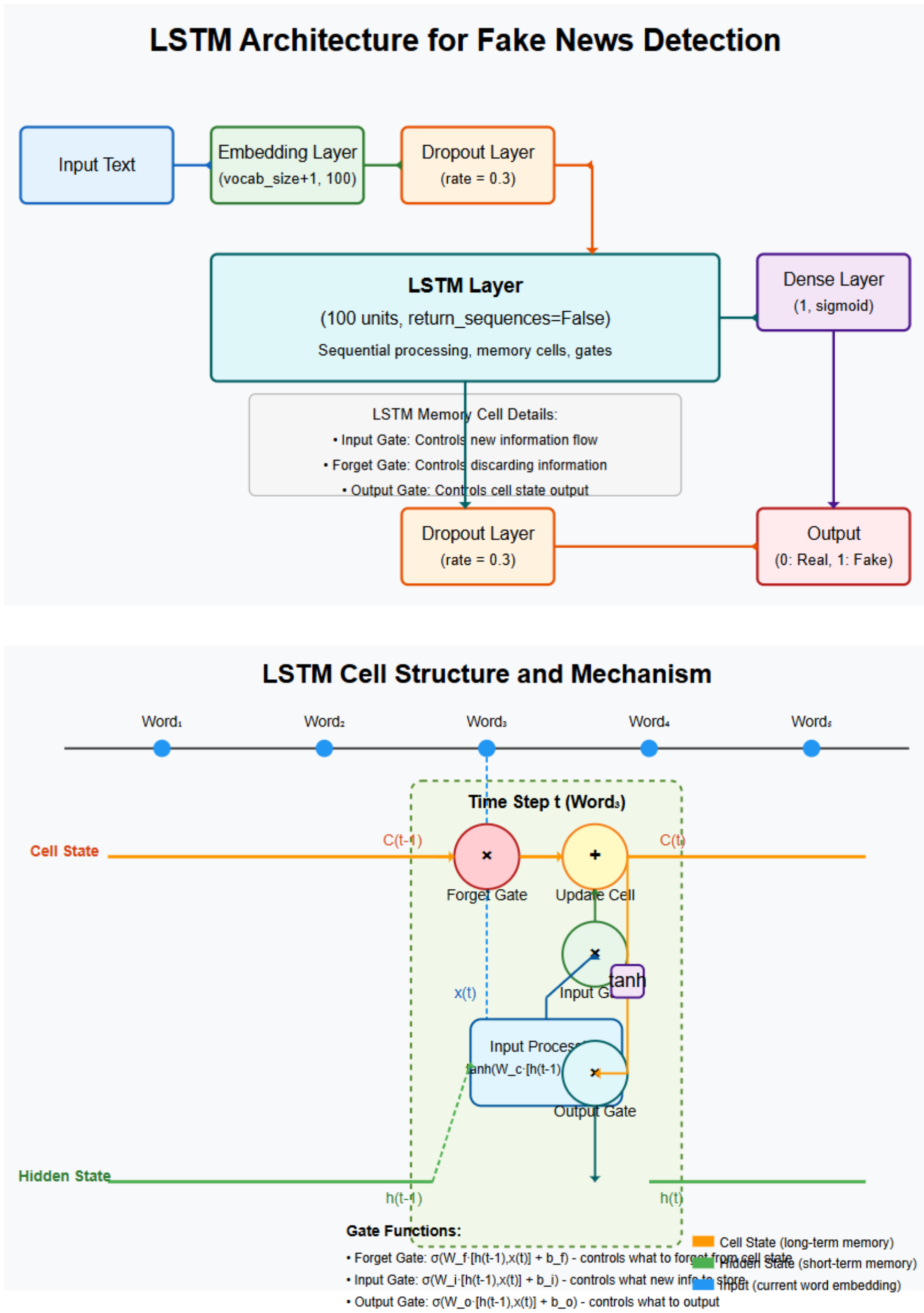

Figure 2: Top: LSTM Architecture for Fake News Detection; Bottom: LSTM Cell Mechanism in LSTM Layer

3.3 Training

- Epochs: 10
- Batch Size: 64
- Accuracy Achieved: **99.41%**

4 BERT-Based Approach

4.1 Preprocessing

- Tokenization using Hugging Face's BERT-base-uncased
- WordPiece encoding
- Max sequence length: 512

4.2 Model Description

- Pre-trained BERT model
- Added a Dense classification layer
- Fine-tuned on fake news dataset

4.3 Training

- Epochs: 3-5
- Batch size: 16/32
- Accuracy Achieved: **99.98%**

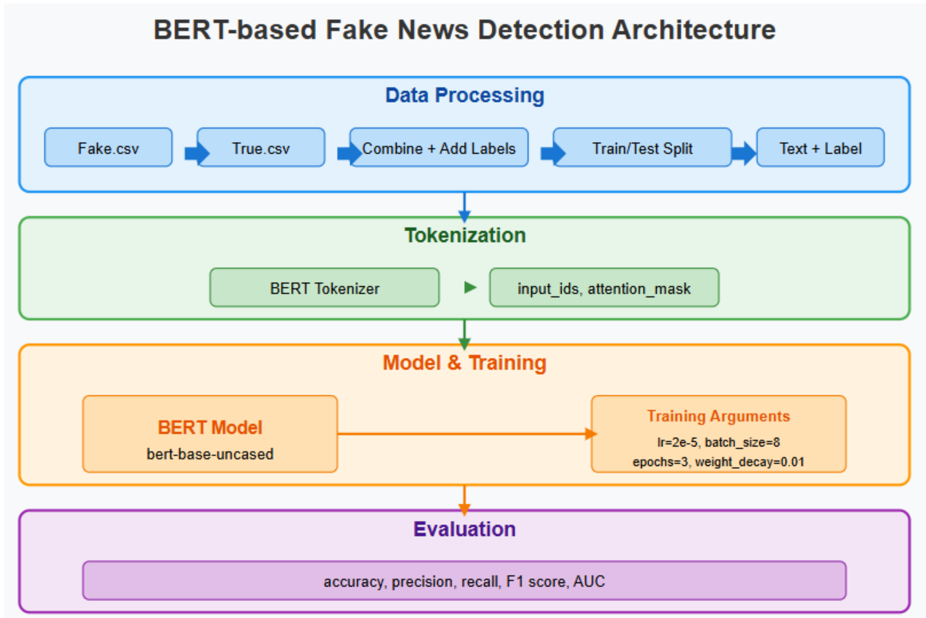

Figure 3: BERT Architecture for Fake News Detection

5 Evaluation and Comparison

5.1 Metrics

- Accuracy
- Confusion Matrix
- F1-Score

5.2 Performance Comparison

Model	Accuracy	Remarks
LSTM	99.41%	Fast, less contextual
BERT	99.98%	High accuracy, better context understanding

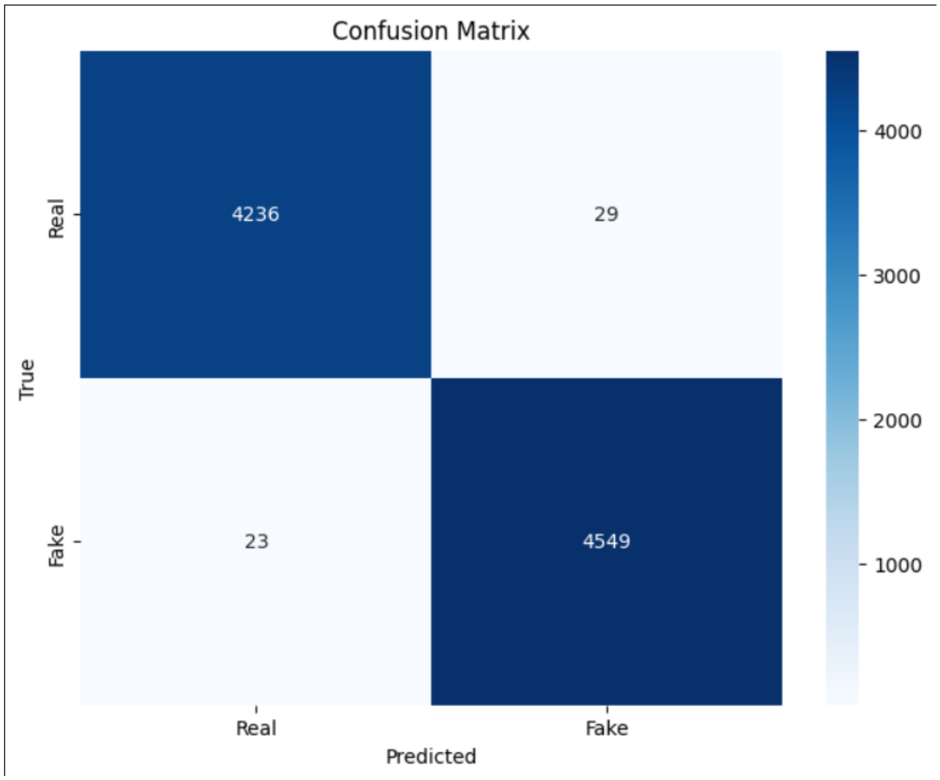

Figure 4: Confusion Matrix of LSTM

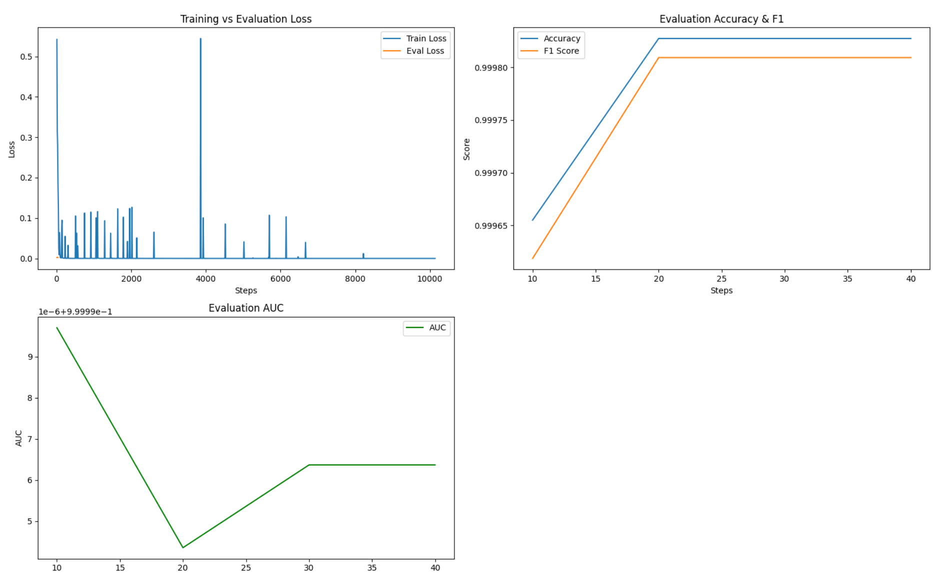

Figure 5: BERT MODEL

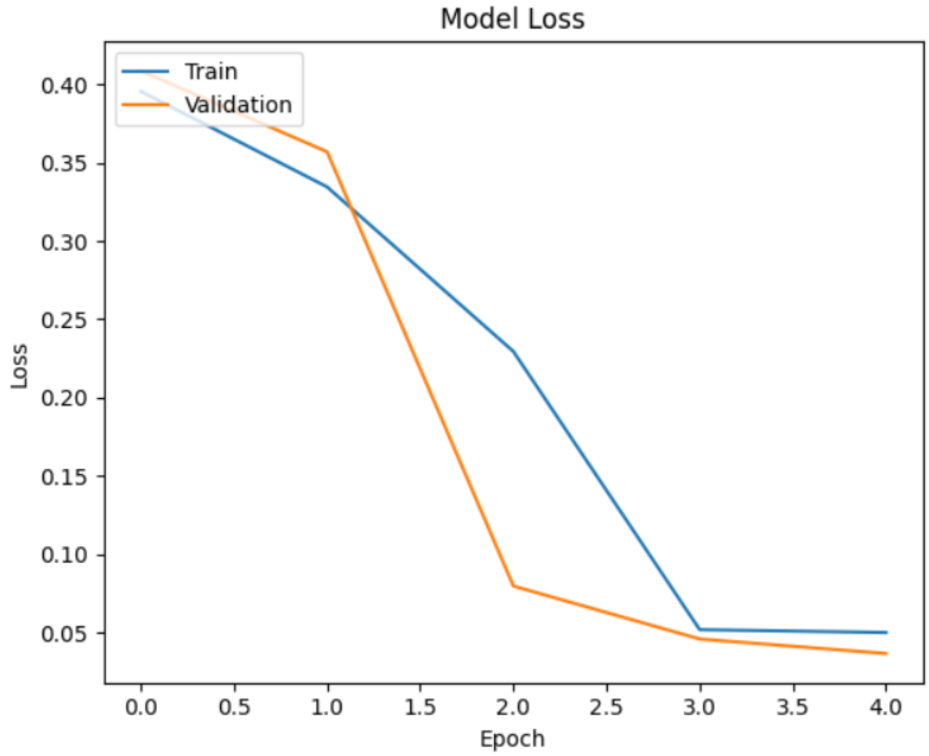

Figure 6: Model loss of LSTM

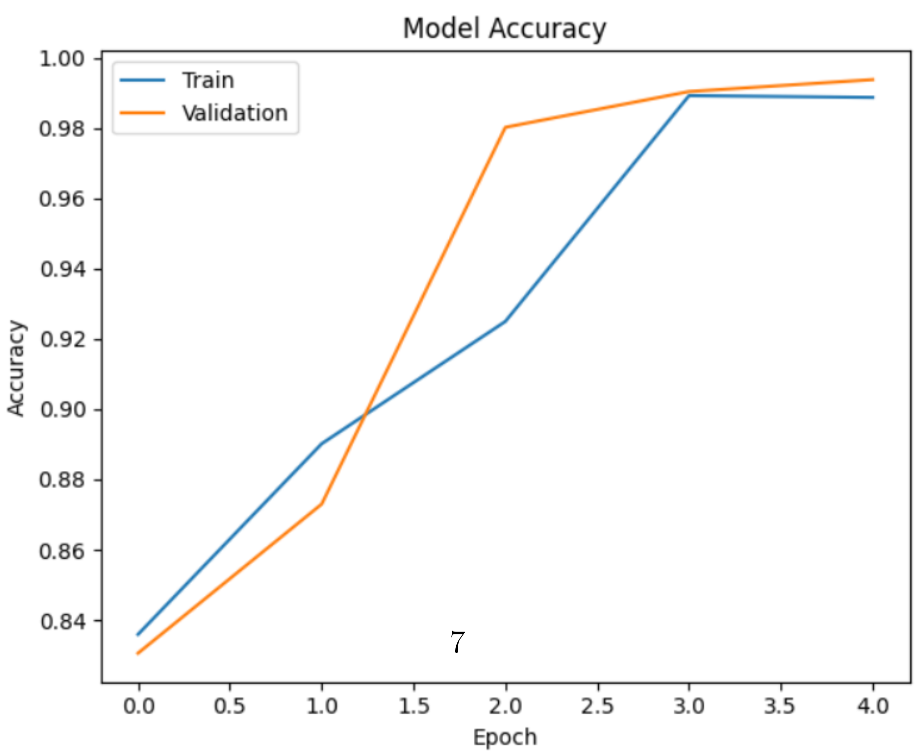

Figure 7: MODEL ACCURACY of LSTM

Classification Report:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4265
1	0.99	0.99	0.99	4572
accuracy			0.99	8837
macro avg	0.99	0.99	0.99	8837
weighted avg	0.99	0.99	0.99	8837

Figure 8: f1 of LSTM

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1	Auc
1	0.000000	0.002382	0.999655	0.999619	0.999619	0.999619	1.000000
2	0.000000	0.002252	0.999827	0.999619	1.000000	0.999809	0.999994
3	0.000000	0.002373	0.999827	0.999619	1.000000	0.999809	0.999996

Figure 9: F1 of BERT

6 Prediction Examples

- **Example 1:** "Scientists claim coffee cures COVID-19"
  - LSTM: Fake (Correct)
  - BERT: Fake (Correct)
- **Example 2:** "The CEO denied fraud allegations."
  - LSTM: Real (Correct)
  - BERT: Real (Incorrect)

Figure 10: Prediction examples

7 Conclusion and Future Work

- BERT outperforms LSTM due to better contextual understanding.
- LSTM remains useful for fast, lightweight implementations.

Future Directions

- Use of advanced models like RoBERTa, XLNet
- Ensemble learning approaches
- Deployment as a web or API service