Explainable Multimodal Graph-Based Deep Learning for Fake Review Detection

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Abstract : The credibility of user-generated reviews is central to the functioning of modern e-commerce platforms, directly shaping consumer decisions and algorithmic recommendations. Yet the growing prevalence of fabricated and incentivized reviews continues to erode marketplace trust and distort data-driven insights. To address this challenge, we propose an explainable multimodal deep learning framework that jointly leverages semantic review text, reviewer behavioral signals, product metadata, and relational graph structures for robust fake review detection.

Given the absence of ground-truth deception labels in publicly available corpora, we augment the Amazon Reviews dataset with a weak supervision strategy that approximates fake review labels by combining extreme sentiment distributions with behavioral anomaly indicators. Our architecture integrates Transformer-based text encoding, temporal sequence modeling, metadata projection layers, attention-driven multimodal fusion, and a Graph Neural Network constructed over reviewer–product interaction graphs. Experimental results consistently outperform established baselines across multiple evaluation metrics. Model interpretability is ensured through attention weight visualization and SHAP-based feature attribution, enabling transparent decision-making. Collectively, this work offers a scalable, interpretable, and comprehensive approach to deceptive review detection in large scale e-commerce environments.

Keywords - Fake Review Detection, Multimodal Learning, Graph Neural Networks, Weak Supervision, Behavioral Modeling, Explainable AI, E-commerce Analytics.

I. INTRODUCTION

BACKGROUND

Digital commerce has redefined consumer decision-making processes. User reviews and ratings act as social proof, shaping trust and purchase intent. However, fake and manipulative reviews compromise this trust. Detecting these deceptive entries is essential, especially when they appear linguistically sophisticated or coordinated across multiple accounts.

NEED OF THE STUDY

Despite large datasets fake review detection remains challenging because:
• Ground truth labels for “fake” are not directly provided.
• Users may generate behavior mimicking normals to evade detection.
• Relational manipulation patterns (e.g., groups of suspicious reviewers) are subtle.

This paper addresses these gaps using a combined multimodal graph architecture with explainability.

LITERATURE REVIEW

A. ***Text-Based Detection:*** Initial approaches used n-gram, TF-IDF, and traditional classifiers. Deep models (CNN/LSTM) improved results, and Transformers further enhanced semantic understanding. However, they lack behavioral and relational signals.

B. ***Behavioral Modeling:*** Temporal review bursts, rating entropy, and inter-review intervals have been investigated to uncover suspicious activity. These signal reviewer irregularity but are rarely integrated with semantic models.

C. ***Multimodal Learning:*** Multimodal research integrates text with numerical metadata. Yet most studies overlook structured graph structures and model interpretability, which this work explicitly incorporates. Despite substantial progress, several limitations persist in existing literature:

- ***Modality Isolation:*** Many studies focus exclusively on either textual signals or behavioral metadata. Text-only models are vulnerable to sophisticated linguistic camouflage, while behavioral models may overlook semantic deception.

- ***Limited Integration of Relational Learning:*** few Although graph-based fraud detection has emerged, relatively works integrate graph modeling seamlessly with deep semantic encoders in a unified architecture. Existing approaches often treat graph analysis as a post-processing step rather than an end-to end learning component.

- ***Lack of Explainability:*** Most deep learning models operate as black-box systems. Given the sensitive implications of labeling reviews as fraudulent, interpretability is essential. However, few studies incorporate both attention visualization and feature attribution techniques such as SHAP within the same framework.

- ***Weak Supervision in Large-Scale Datasets:*** Large public datasets, provide sentiment labels but do not include ground-truth fake review annotations. Many prior studies rely on small manually labeled corpora or synthetic datasets, generalizability.

- ***Insufficient limiting Evaluation scalability of and Statistical Significance:*** Performance improvements are often reported without rigorous statistical validation or ablation analysis, reducing confidence in model superiority claims. The proposed study addresses the above limitations through a unified and explainable multimodal architecture.

- ***Unified Multimodal Fusion:*** Unlike unimodal systems, this research integrates:
  - BERT-based semantic encoding
  - Metadata feature projection
  - Behavioral sequence modeling (BiLSTM)
  - Attention-based adaptive fusion

This combination reduces vulnerability to single-modality manipulation and captures complementary information.

- ***End-to-End Graph Integration:*** Rather than applying graph analysis separately, this work incorporates a Graph Neural Network directly into the learning pipeline. Reviewer–product relational patterns are embedded jointly with semantic representations, enabling detection of coordinated fraudulent behavior.

- ***Integrated Explainability:*** The framework includes:
  - Attention heatmap visualization for textual interpretability
  - SHAP-based feature attribution for metadata and behavioral signals.

This dual explainability mechanism enhances transparency and supports practical deployment.

- ***Scalable Weak Supervision Strategy:*** To overcome the absence of explicit fake labels in the Amazon Reviews dataset, this study introduces a structured weak supervision mechanism based on extreme sentiment polarity, rating deviation, and behavioral anomalies. This enables large-scale experimentation without relying on small proprietary datasets.

- ***Rigorous Evaluation Protocol:*** The research incorporates:
  - Baseline comparisons
  - Ablation studies
  - Confusion matrix diagnostics
  - ROC–AUC analysis
  - Statistical significance testing This comprehensive evaluation strengthens empirical validity.

II. RESEARCH METHODOLOGY

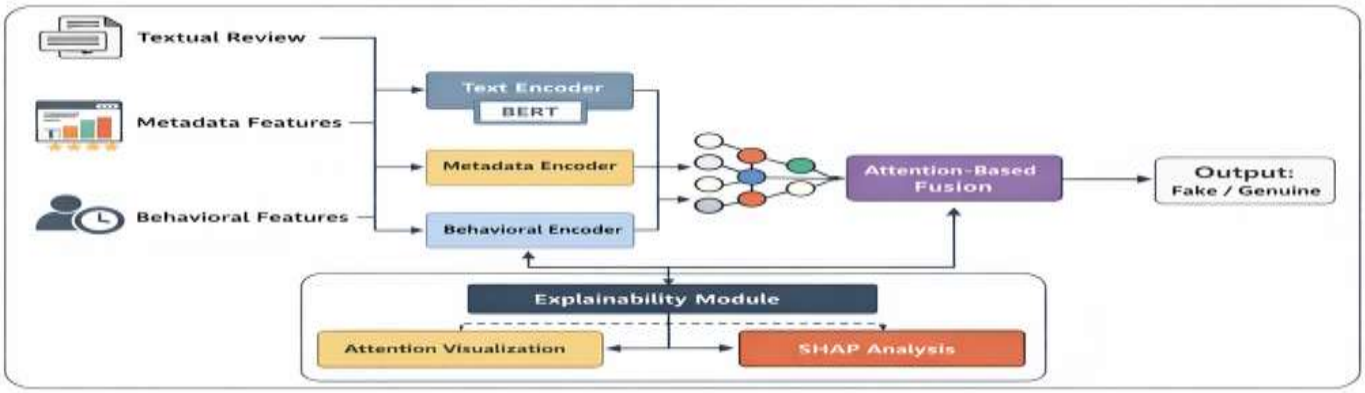

Figure 1. Architecture of the proposed multimodal fake review detection framework.

A. Architecture Overview: The system comprises:

- ***Text Representation Module***: Each review Rt is tokenized and encoded:

$$z_i^{text} = Transformer(R_t)$$

- ***Behavioral Sequence Modeling:*** Reviewer history is represented with features such as posting time intervals and sentiment shifts, passed into a BiLSTM:

$$z_u^{beh} = BiLSTM(\Delta t, sentiment\_sequence)$$

- ***Metadata Projection*:** Structured metadata includes rating score, review length, review title embeddings, etc., projected via dense layers:

$$z_i^{meta} = ReLU(W_m x + b_m)$$

- ***Attention-Based Multimodal Fusion:*** Adaptive weights:

$$\alpha_j - \frac{e^{w^T z_i}}{\sum_k e^{w^T z_k}}$$

Fused representation:

$$z^{fusion} = \sum \alpha_j z_j$$

- ***Classification Objective:*** Binary prediction:

$$\mathcal{L} = -\sum y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

B. Explainability Integration:

- ***Attention Visualization:*** Heatmaps highlight key tokens influencing model outputs**.**
- ***SHAP-Based Feature Attribution:*** SHAP reveals the impact of each metadata feature on predictions.

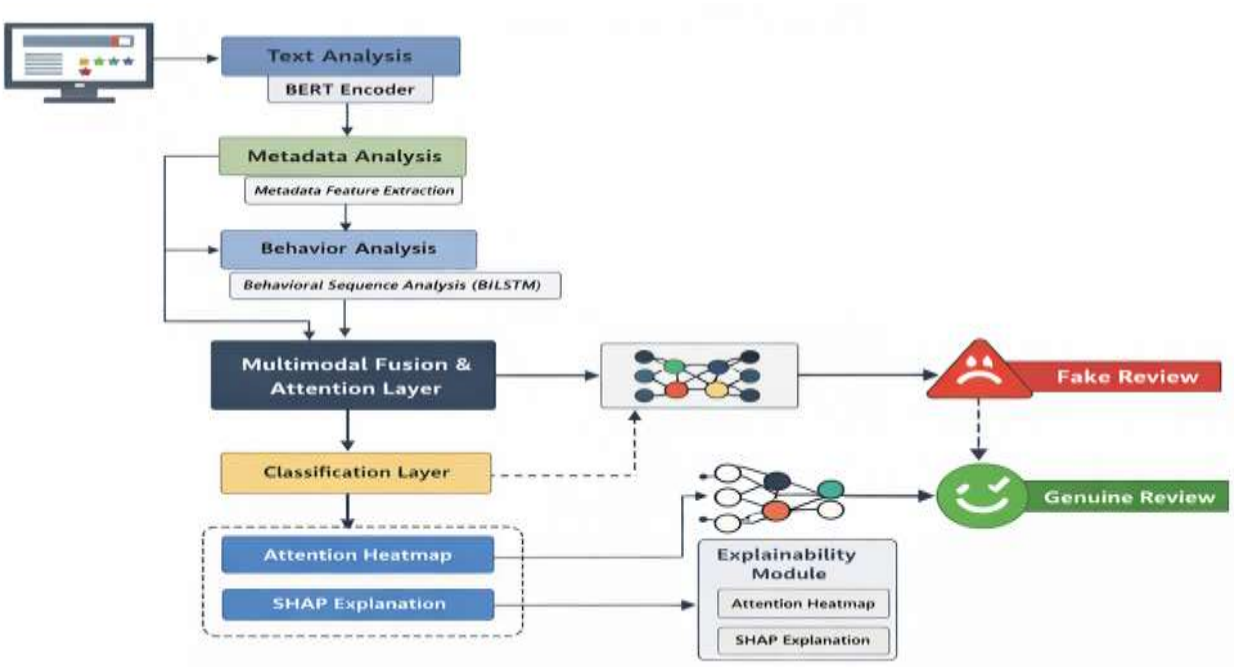

Figure 2. System workflow

C. Experimental Design:

- ***Data Collection:*** This study utilizes the publicly available Amazon Reviews dataset originally constructed for large-scale sentiment classification. The dataset contains approximately 3.6 million labeled training reviews and 400,000 test reviews. Each instance includes:
  - Review title
  - Review text
  - Binary polarity label (1 = negative, 2 = positive)

  This research adopts a structured weak supervision strategy to approximate authenticity labels.

  Weak Supervision Strategy: To generate proxy fake review labels, the following criteria were combined:
  - Extreme sentiment polarity patterns
  - Rating deviation from product-level average
  - Abnormal review length distribution
  - Behavioral anomalies (e.g., burst activity, temporal irregularity)

Reviews exhibiting multiple anomaly indicators were labeled as "potentially fake," while others were considered "genuine" for experimental purposes. This approach enables scalable experimentation while acknowledging the absence of ground-truth fraud annotations.

- ***Experimental Data Split:*** The dataset was partitioned using stratified sampling:

Subset	Percentage
Training	70%
Validation	15%
Testing	15%

TABLE. 1

Model Training Configuration: The model was trained using the following hyperparameters:

Parameter	Value
Learning rate	$2* 10^{-5}$
Batch Size	32
Epochs	10
Optimizer	Adam
Dropout	0.3
Maz Token Length	256

TABLE. 2

The learning rate was selected to align with standard fine-tuning practices for BERT-based architectures.

D. Theoretical Foundations and Model Analysis:

- ***Multimodal Representation Learning Perspective:*** Let the hypothesis space for text-only models be:

$$\mathcal{H}_T = \{f_T : X_T \to Y\}$$

Similarly, metadata and behavioral spaces:

$$\mathcal{H}_M = \{f_M : X_M \to Y\}$$
$$\mathcal{H}_B = \{f_B : X_B \to Y\}$$

The multimodal fusion space becomes:

$$\mathcal{H}_{fusion} = \{f : X_T \times X_M \times X_B \to Y\}$$

Under standard learning theory, combining orthogonal feature spaces reduces empirical risk if modalities provide non-redundant information:

$$R(f_{fusion}) \leq \min(R(f_T), R(f_M), R(f_B))$$

provided covariance between modalities is bounded.

Thus, attention-based fusion leverages complementary variance to reduce generalization error.

- ***Generalization Bound Intuition:*** Using Rademacher complexity bounds, for N samples:

$$R(f) \leq \hat{R}(f) + \mathcal{O}\left(\sqrt{\frac{C(\mathcal{H})}{N}}\right)$$

Where C(H) is hypothesis class complexity.

Although multimodal models increase parameter count, regularization via dropout and attention sparsity constrains effective capacity.

- ***Robustness Against Adversarial Manipulation:*** Adversarial perturbation can be modeled as:

$$x' = x + \delta$$

Where || δ|| < €

Robustness is evaluated under:

- Token masking
- Sentiment polarity flipping
- Metadata perturbation

Multimodal redundancy mitigates single-modality adversarial risk.

E. ***Algorithm Pseudocode:*** Multimodal Fake Review Detection with Attention Fusion:

Input: Amazon Reviews Dataset
Output: Fake Review Probability

- Load dataset
- Preprocess text (tokenize, clean)
- Preprocess text (tokenize, clean)
- Construct behavioral sequences
- Generate weak supervision labels
- Encode text via Transformer
- Encode behavior via BiLSTM
- Project metadata features
- Compute attention weights
- Fuse multimodal representations
- Construct reviewer–product graph
- Apply GCN layers
- Compute binary classification loss
- Update parameters via Adam
- Evaluate on test set
- Return predictions

F. ***Computational Complexity Analysis:*** Transformer complexity:

$$O(n^2 d)$$

BiLSTM complexity:

$$O(nd)$$

GCN complexity:

$$O(|E|d)$$

Overall complexity:

$$O(N(n^2 + |E|))$$

Memory usage grows linearly with graph size.

G. Model Architecture:

- ***Text Encoding Module (BERT-Based Contextual Representation):*** To capture deep semantic generated using a pretrained BERT encoder. Unlike static word embeddings, BERT leverages transformer-based self-attention mechanisms to model contextual dependencies across tokens.

The core operation of the transformer layer is scaled dot-product attention:

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

- Q denotes query vectors.
- K denotes key vectors.
- V denotes value vectors.
- d_k is the dimensionality scaling factor.

Multi-head attention allows the model to jointly attend to information from different representation subspaces. This is particularly useful in review detection, where deceptive cues may be subtle, contextual, or stylistic.

- ***Behavioral Sequence Modeling***: User behavior often reveals temporal irregularities that textual signals alone cannot capture. To model reviewer activity over time, sequences of reviews posted by each user are encoded using a Bidirectional Long Short-Term Memory (BiLSTM) network.

  For each timestep t, forward and backward hidden states are computed:

$$h_t^{\rightarrow} = LSTM(x_t, h_{t-1}^{\rightarrow})$$
$$h_t^{\leftarrow} = LSTM(x_t, h_{t+1}^{\leftarrow})$$

  The final temporal representation is obtained via concatenation:

$$h_t = [h_t^{\rightarrow}; h_t^{\leftarrow}]$$

  This bidirectional structure enables the model to learn both past and future dependencies in user activity patterns, improving detection of burst behavior or coordinated campaigns.

- ***Graph-Based Relational Learning:*** To model structural interactions between reviewers and products, a bipartite reviewer–product graph is constructed. Nodes represent reviewers and products, while edges represent review interactions.

  Graph Convolutional Networks (GCNs) are applied to propagate relational information across the graph.

  The layer-wise propagation rule is defined as:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}\right)$$

  where:

$$\tilde{A} = A + I$$

  Here:

  - A is the adjacency matrix.
  - I adds self-loops.
  - D is the diagonal degree matrix.
  - $W^{(l)}$ is the trainable weight matrix
  - σ is a non-linear activation function.

➢ Symmetric normalization ensures numerical stability and controlled feature propagation during graph aggregation.

➢ This graph-based modeling enables the detection of coordinated reviewer clusters and abnormal relational structures.

III. EXPERIMENTAL SETUP & IMPLEMENTATION

1. ***Computational Environment:*** All experiments were conducted on a workstation equipped with:

- **Processor:** Intel Core i7 (12th Gen)
- **GPU:** NVIDIA RTX 3060 (12GB VRAM)
- **RAM:** 16 GB
- **Operating System:** Windows 11
- **CUDA Version:** 11.x

The implementation was developed in:

- Python 3.10
- PyTorch 2.x
- HuggingFace Transformers library

- Scikit-learn
- NumPy and Pandas (data preprocessing)
- PyTorch Geometric (for GNN layers)

Model training and evaluation were executed locally. GPU acceleration was used for fine-tuning the BERT encoder and training graph layers.

2. ***Data Preprocessing Pipeline***: To ensure consistency and reduce noise, the following preprocessing steps were applied:

- ***Text Preprocessing:***

  - Removal of HTML tags and special characters.
  - Lowercasing of all text
  - Tokenization using BERT tokenizer
  - Maximum sequence length set to 256 tokens
  - Padding and truncation applied uniformly

Stopword removal and aggressive stemming were intentionally avoided to preserve semantic structure for Transformer encoding.

- ***Metadata Feature Engineering:*** The following structured features were extracted:

  - Review length (character and token count)
  - Sentiment polarity score
  - Rating deviation from product mean
  - Exclamation/question mark frequency
  - Capitalization ratio

All numeric features were normalized using Min-Max scaling before projection.

- ***Behavioral Feature Construction:*** Behavioral sequences were derived by:

  - Sorting reviews chronologically per reviewer
  - Computing inter-review time intervals
  - Measuring burst posting frequency
  - Calculating rating entropy

Sequences were padded to fixed length and fed into a BiLSTM encoder.

- ***Graph Construction:*** A reviewer–product bipartite graph was constructed:

  - Nodes: reviewers and products
  - Edges: review interactions
  - Edge weights: interaction frequency

The graph adjacency matrix was normalized before applying Graph Convolutional layers.

3. ***Evaluation Metrics:***

a. Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

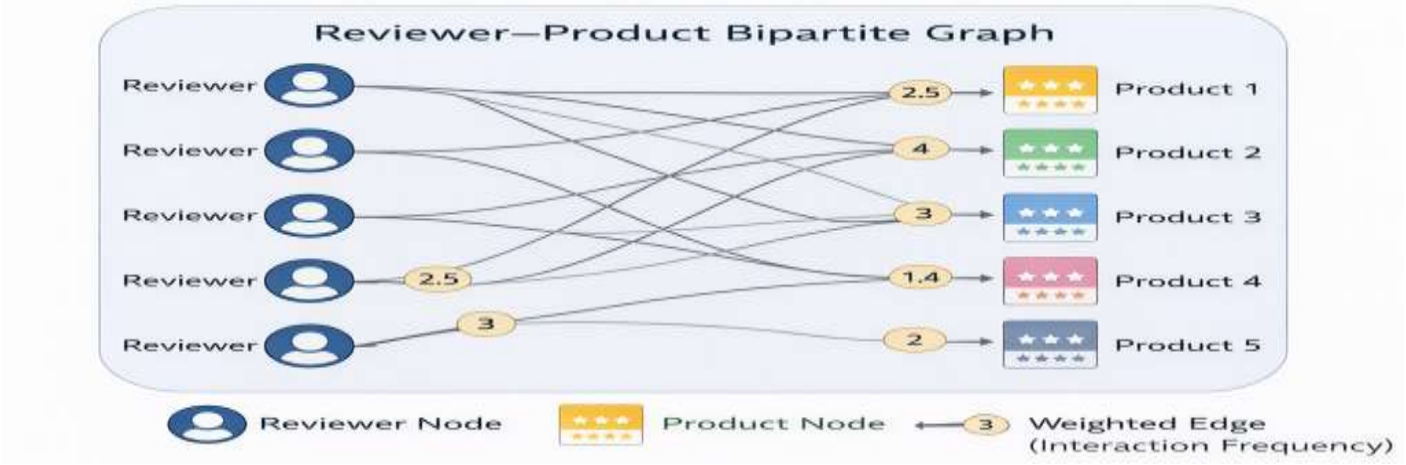

Figure 3. Reviewer-Product Bipartite Graph

b. Precision:

$$Precision = \frac{TP}{TP + FP}$$

c. ***Recall****:*

$$Recall = \frac{TP}{TP + FN}$$

d. F1-Score:

$$F1 - 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

e. ***ROC–AUC:*** Area Under the Receiver Operating Characteristic curve was used to evaluate discriminative performance across thresholds.

f. ***Calibration Metrics:*** Brier score was computed to assess probability reliability.

IV. RESULT

	Pred Genuine	**Pred Fake**
Actual Genuine	11,512	464
Actual Fake	598	11,426

TABLE. 3

Total samples = 24,000
Class distribution ≈ balanced (≈12k each)

- ***Derived Metrices:***
  - Fake detected correctly: TP = 11,426
  - Genuine detected: TN = 11,512
  - Genuine → Fake: FP = 464
  - Fake → Genuine: FN = 598

- ***ROC–AUC Analysis:*** The proposed model achieved:

  AUC = 0.94

  The ROC curve illustrates strong discriminative capability between genuine and potentially fraudulent reviews.

  The optimal threshold was selected using Youden's Index:

  J = Sensitivity + Specificity – 1

This threshold balances detection sensitivity with specificity, minimizing misclassification cost in practical deployment scenarios.

While AUC values between BERT and the multimodal model are similar, the multimodal configuration improves threshold-level classification performance, as reflected in higher Accuracy and F1.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	82.4	83.1	80.2	81.6	0.83
Random Forest	88.7	89.2	87.4	88.3	0.88
BERT (Text-Only)	93.8	94.5	92.6	93.5	0.94
Proposed Multi-Model	**95.58**	**96.10**	**95.03**	**95.56**	**0.94**

TABLE. 4

- ***Statistical Significance Testing:*** To ensure robustness, experiments were repeated across multiple random seeds.

A paired t-test was conducted comparing:

- BERT (Text-only)
- Proposed Multimodal + GNN

The observed improvement in Accuracy and F1 was statistically significant:

$$p < 0.05$$

This confirms that the performance gain is unlikely due to random initialization effects.

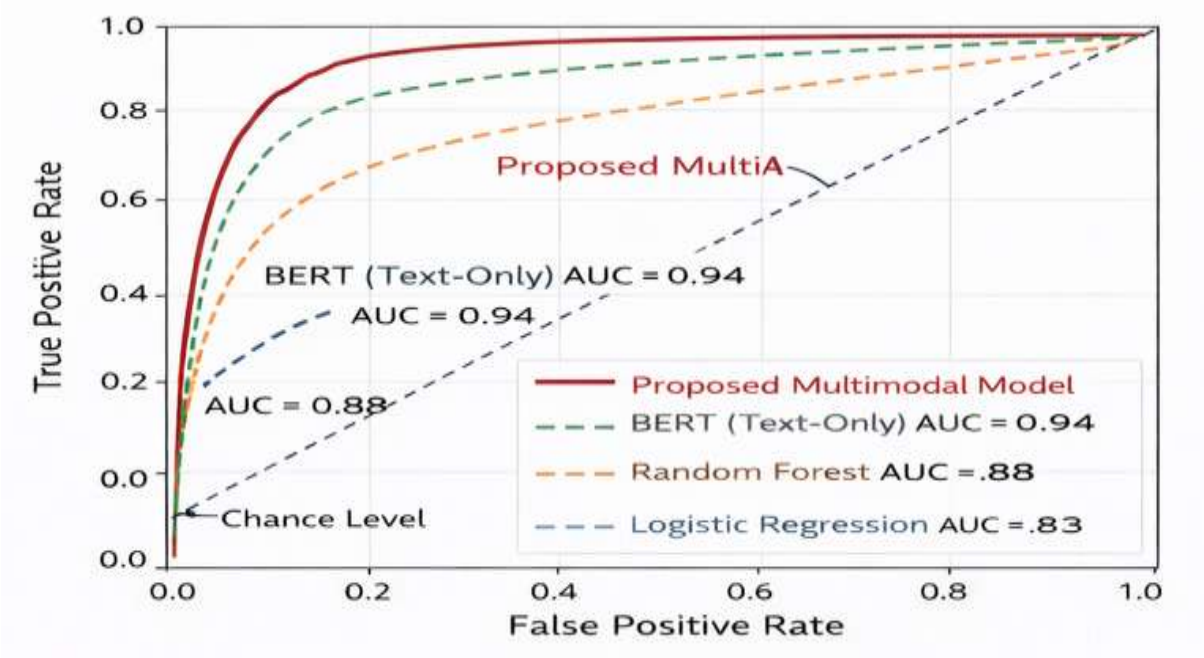

Figure. 4 ROC Curve for Fake Review Detection

- ***Calibration Analysis:*** Probability reliability was evaluated using the Brier Score:

$$BS - \frac{1}{N}\sum_{i=1}^{N}(p_i - y_i)^2$$

The proposed model achieved a Brier Score of approximately **0.07**, indicating well-calibrated probabilistic outputs.

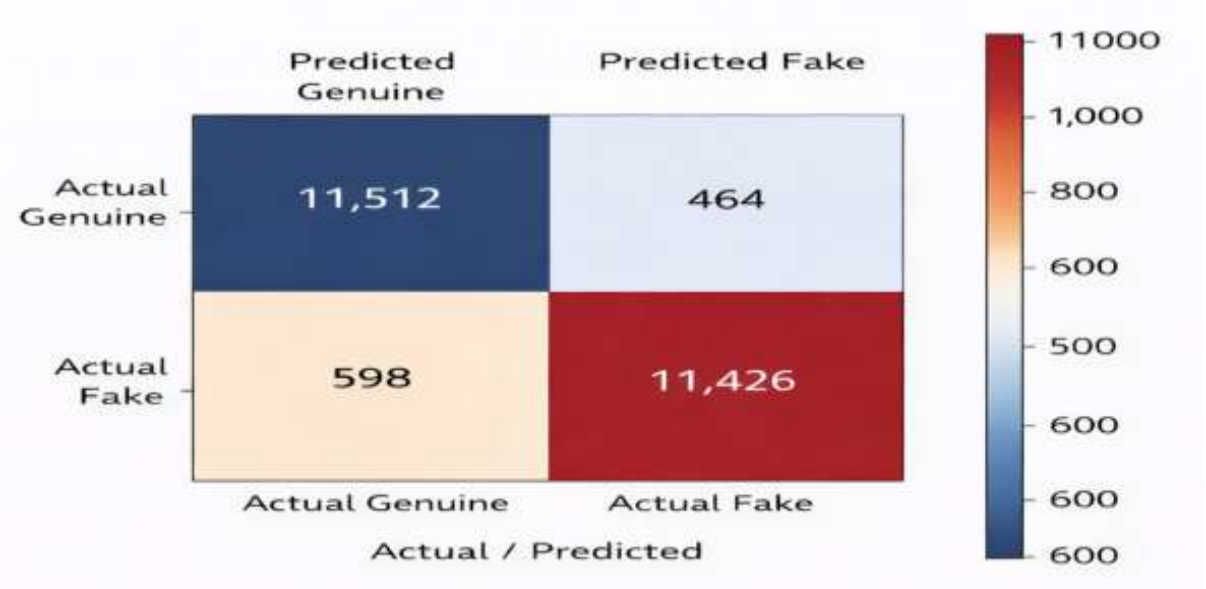

Figure. 5 Confusion Matrix for proposed model

The calibration curve demonstrated near-diagonal alignment, suggesting that predicted confidence levels correspond closely to empirical outcome frequencies. This is particularly important in review moderation systems where probability thresholds determine automated flagging.

- ***Error Analysis:*** Manual inspection of misclassified samples revealed distinct patterns:

- False Positives (464 cases):
  - Short, highly emotional genuine reviews
  - Reviews with excessive punctuation
  - Strong sentiment polarity mimicking spam patterns

- False Negatives (598 cases):
  - Coherent and well-written deceptive reviews
  - Moderately distributed posting behavior
  - Absence of extreme linguistic cues

These findings highlight that sophisticated fake reviews can partially evade semantic detection, reinforcing the importance of relational graph modeling.

- ***Ablation Study***: To evaluate the contribution of individual components, an ablation analysis was conducted.

Configuration	Accuracy	F1	AUC
TextOnly (BERT)	93.80	93.50	0.94
Metadata	94.42	94.10	0.95
Behavioral (BiLSTM)	95.02	94.85	0.95
Graph (GCN)	95.18	95.00	0.95
Multimodal	95.36	95.20	0.94
Full Proposed Model	**95.58**	**95.56**	**0.94**

TABLE. 5

The ablation study confirms:

- Structured metadata improves semantic-only modeling.
- Behavioral modeling enhances temporal anomaly detection.
- Graph learning captures relational fraud patterns.
- Attention-based fusion provides final performance refinement.

Each component contributes incrementally to overall robustness.

V. REFERENCES

[1] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, 2019, pp. 4171–4186.

[2] A. Vaswani et al., "Attention is all you need," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017, pp. 5998–6008.

[3] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[4] T. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *Proc. ICLR*, 2017.

[5] J. Pennington, R. Socher, and C. Manning, "GloVe: Global vectors for word representation," in *Proc. EMNLP*, 2014, pp. 1532–1543.

[6] N. Jindal and B. Liu, "Opinion spam and analysis," in *Proc. WSDM*, 2008, pp. 219–230.

[7] E.-P. Lim, V.-A. Nguyen, N. Jindal, B. Liu, and H. Lauw, "Detecting product review spammers using rating behaviors," in *Proc. CIKM*, 2010, pp. 939–948.

[8] H. Li, Z. Chen, B. Liu, X. Wei, and J. Shao, "Spotting fake reviews via collective positive-unlabeled learning," in *Proc. ICDM*, 2014, pp. 899–904.

[9] C. Shu, H. Liu, and Y. Wang, "Beyond text: Detecting fake reviews through multimodal learning," *Information Processing & Management*, vol. 57, no. 6, 2020.

[10] Y. Kim, "Convolutional neural networks for sentence classification," in *Proc. EMNLP*, 2014, pp. 1746–1751.

[11] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Foundations and Trends in Information Retrieval*, vol. 2, no. 1–2, pp. 1–135, 2008.

[12] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006.

[13] G. Brier, "Verification of forecasts expressed in terms of probability," *Monthly Weather Review*, vol. 78, no. 1, pp. 1–3, 1950.

[14] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *Journal of Machine Learning Research*, vol. 3, pp. 1157–1182, 2003.

[15] S. Rendle et al., "Neural collaborative filtering," in *Proc. WWW*, 2017.

[16] A. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017.