AI Detection Hub

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Abstract—This project proposes a Multimodal Ensemble-Based Fake Media Detection Framework to identify fake and AI-generated content across text, image, audio, and video.
It addresses the growing threat of deepfakes and misinformation caused by generative AI. The system uses TF-IDF–based machine learning for text classification. Transformer-based models are applied for image and audio deepfake detection.
Video analysis combines frame and audio verification through multimodal fusion. Ensemble majority voting improves accuracy and reduces model bias. Experimental results show higher performance compared to single-modality models. The system is deployed as a real-time web application for practical media authentication.

Keywords—Deepfake Detection, Fake News Detection, Multimodal AI, Ensemble Learning, Media Authentication.

I. Introduction

The rapid advancement of Artificial Intelligence has enabled the creation of realistic fake news, AI-generated images, cloned speech, and deepfake videos. These technologies threaten digital trust, cybersecurity, and information integrity. Misinformation spreads quickly through social media, influencing public opinion and society. Traditional detection systems are unimodal and focus on only one type of data. Such systems fail to detect inconsistencies across text, image, audio, and video.

To overcome this limitation, a Multimodal Ensemble-Based Fake Media Detection Framework is proposed. The system integrates multiple modalities within a unified architecture. Ensemble voting and confidence aggregation improve accuracy and enable real-time media authentication. This approach enhances robustness by leveraging complementary information from different data sources. It provides a scalable and practical solution for combating AI-generated misinformation in real-world applications.

II. Literature Review

The rapid rise of fake news and deepfake technologies has significantly increased research in automated media authentication. Early fake news detection methods relied on traditional machine learning algorithms such as Logistic Regression, Support Vector Machines, and Random Forest using TF-IDF features for text classification. The LIAR dataset introduced by William Yang Wang supported supervised misinformation detection research. With the advancement of deep learning, models like LSTM and BERT developed by Jacob Devlin improved contextual understanding in text analysis. In the visual domain, the introduction of GANs by Ian Goodfellow enabled highly realistic synthetic image and video generation. Datasets such as Face Forensics++ supported CNN and transformer-based deepfake detection models, while ASVspoof provided benchmarks for audio spoof detection using MFCC and deep neural networks.

Although these unimodal approaches achieved strong performance within individual domains, they often fail to detect cross-modal inconsistencies in real-world multimedia content. However, these unimodal approaches cannot effectively detect cross-modal inconsistencies in real-world multimedia content.

III. Materials and Methods

A well-structured methodology is essential to ensure reproducibility and clarity of the proposed Multimodal Ensemble-Based Fake Media Detection Framework. The methods adopted in this research are described in detail to enable replication by other researchers. The framework integrates text, image, audio, and video analysis within a unified architecture using machine learning, deep learning, and ensemble fusion techniques.

1) Data Preprocessing: -

The system utilizes heterogeneous datasets across multiple modalities. Preprocessing ensures data consistency and quality before model training.

Numbered steps involved in preprocessing:

- Text cleaning and TF-IDF feature extraction
- Image resizing and normalization
- Audio resampling (16 kHz) and spectral feature extraction
- Video decomposition into frames and audio streams.

2) Model Development: -

Separate models are developed for each modality to extract meaningful features and perform classification.

- Text classification using Machine Learning (Logistic Regression/SVM)
- Image detection using transformer-based models
- Audio deepfake detection using spectral features and deep learning
- Video analysis through frame and audio verification.

3) Ensemble Fusion and Evaluation: -

To enhance robustness and reduce bias, ensemble learning is applied.

- Majority voting for final prediction
- Confidence score aggregation
- Evaluation using Accuracy, Precision, Recall, F1-Score, and ROC-AUC with 70-15-15 data split.

4) Implementation and Evaluation: -

The system is implemented using Python with Scikit-learn, PyTorch, and Transformer libraries and deployed via a Flask web application.

Model performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC and Confusion Matrix analysis

A 70% training, 15% validation, and 15% testing split is used to ensure fair and reproducible evaluation.

IV. Result and Discussion

The proposed multimodal framework achieved higher accuracy compared to individual text, image, and audio models. While unimodal models performed well independently, they showed limitations in detecting cross-modal manipulations. By combining predictions using majority voting and confidence aggregation, the ensemble model improved reliability and reduced false classifications. Overall, the results confirm that multimodal fusion enhances robustness and provides an effective solution for real-time fake media detection.

A. Figures and Tables (Subsection Level 2)

This figure illustrates the overall architecture of the proposed Multimodal Ensemble-Based Fake Media Detection Framework, showing input processing, modality-specific models, ensemble fusion, and final classification output.

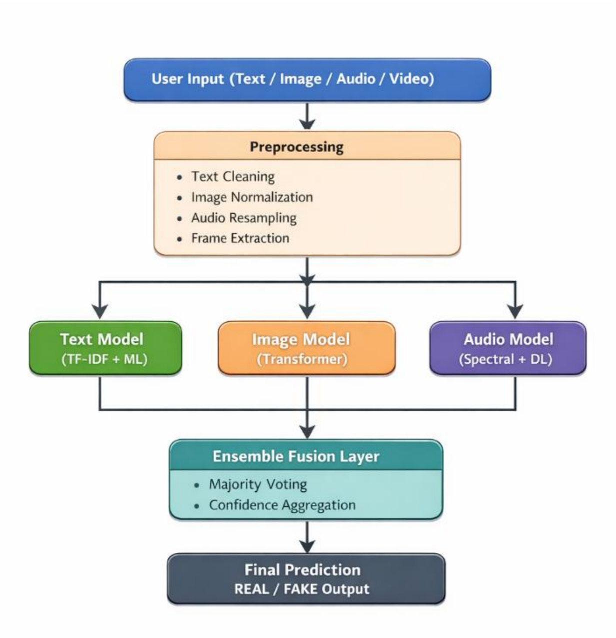
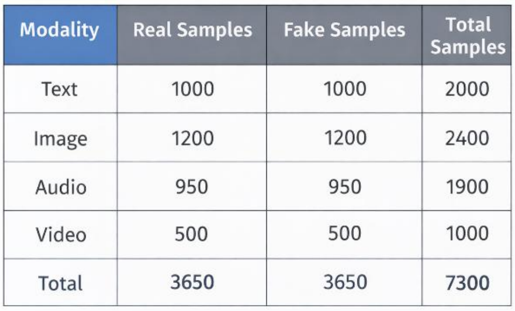


Fig. 1. Multimodal Ensemble-Based Fake Media Detection Architecture.

Table 1. Dataset Distribution Across Modalities

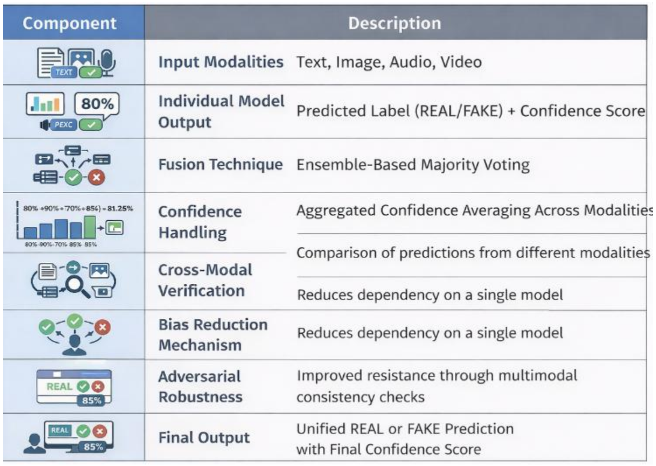


Modality	Real Samples	Fake Samples	Total Samples
Text	1000	1000	2000
Image	1200	1200	2400
Audio	950	950	1900
Video	500	500	1000
Total	3650	3650	7300

1. Multimodal Fusion Strategy Overview (Subsection (Level 3)

To enhance detection reliability, predictions from individual modalities are combined using an ensemble-based fusion mechanism. Each model generates a classification label along with a confidence score. Majority voting is applied to determine the final class label, while confidence aggregation ensures more reliable decision-making. This cross-modal verification approach reduces bias from individual models and improves resistance to adversarial manipulation. The fusion strategy strengthens overall system robustness and enables consistent performance across diverse multimedia inputs.

Multimodal Fusion Strategy Overview: -

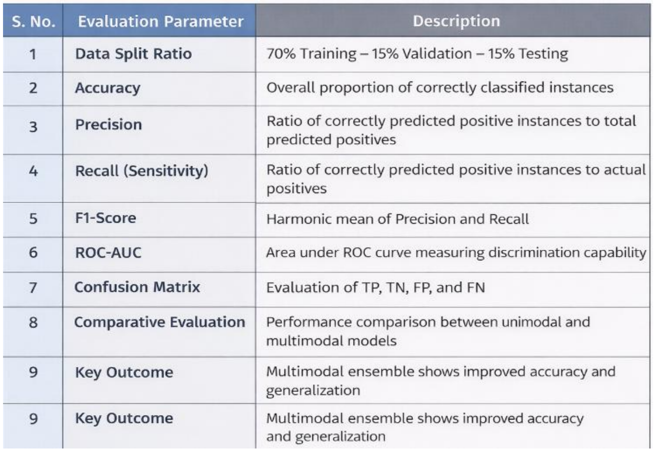


Component	Description	
TEXT ✓	Input Modalities	Text, Image, Audio, Video
80% PEXC ✓	Individual Model Output	Predicted Label (REAL/FAKE) + Confidence Score
✓ ✗	Fusion Technique	Ensemble-Based Majority Voting
80% +90%+70%+854) = 81.25% 80% 90% 70% 85% 95%	Confidence Handling	Aggregated Confidence Averaging Across Modalities
	Cross-Modal Verification	Comparison of predictions from different modalities Reduces dependency on a single model
✓ ✓ ✗	Bias Reduction Mechanism	Reduces dependency on a single model
REAL ✓ ✗ 85%	Adversarial Robustness	Improved resistance through multimodal consistency checks
REAL ✓ ✗ 85%	Final Output	Unified REAL or FAKE Prediction with Final Confidence Score

2. Performance Evaluation (Subsection Level 3).

The system performance is evaluated using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. A 70%–15%–15% train-validation-test split is applied to ensure fair evaluation. Confusion matrices are used to analyze false positives and false negatives across modalities. Comparative experiments demonstrate that the multimodal ensemble framework outperforms individual unimodal models, achieving higher overall accuracy and improved generalization capability. The evaluation confirms the effectiveness of multimodal integration for real-time fake media detection.

Performance Evaluation Metrics and Experimental Setup: -



S. No.	Evaluation Parameter	Description
1	Data Split Ratio	70% Training – 15% Validation – 15% Testing
2	Accuracy	Overall proportion of correctly classified instances
3	Precision	Ratio of correctly predicted positive instances to total predicted positives
4	Recall (Sensitivity)	Ratio of correctly predicted positive instances to actual positives
5	F1-Score	Harmonic mean of Precision and Recall
6	ROC-AUC	Area under ROC curve measuring discrimination capability
7	Confusion Matrix	Evaluation of TP, TN, FP, and FN
8	Comparative Evaluation	Performance comparison between unimodal and multimodal models
9	Key Outcome	Multimodal ensemble shows improved accuracy and generalization
9	Key Outcome	Multimodal ensemble shows improved accuracy and generalization

B. References

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C. Footnotes

Footnotes should be numbered consecutively using superscripts and placed after punctuation marks. They should be used sparingly and only for brief explanatory information that does not fit naturally in the main text. References must not be included in footnotes and should instead be cited using numbered square brackets in the reference list. In IEEE format, footnotes appear at the bottom of the column in a smaller font size.

D. Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even if they have already been defined in the abstract. Write the full term first, followed by the abbreviation in parentheses. After that, use only the abbreviation throughout the paper. Do not use abbreviations in the title unless they are unavoidable. Commonly accepted abbreviations such as IEEE, AI, CNN, and URL do not need to be defined.

E. Equations

$$E=mc2 \qquad (1)$$

Equation (1) expresses the mass–energy equivalence principle. In this equation, E represents energy, m denotes mass, and c is the speed of light in vacuum. It shows that mass can be converted into energy, and even a small amount of mass corresponds to a large amount of energy because the speed of light is squared.

$$F=ma \qquad (2)$$

Equation (2) represents Newton's Second Law of Motion. Here, F denotes force, m represents mass, and a is the acceleration produced. This equation states that the force applied to an object is directly proportional to its mass and acceleration, meaning greater force results in greater acceleration for a given mass.

F. Other Recommendations

Use consistent formatting throughout the paper and strictly follow the prescribed template. Ensure that figures and tables are properly labeled, numbered consecutively, and referenced in the text before they appear. Place figure captions below figures and table titles above tables. All text should be clear, concise, and grammatically correct. Avoid excessive use of bold or italic formatting, and maintain uniform font style and size as specified in the guidelines. Carefully proofread the manuscript to eliminate typographical and formatting errors before submission.

V. Conclusion

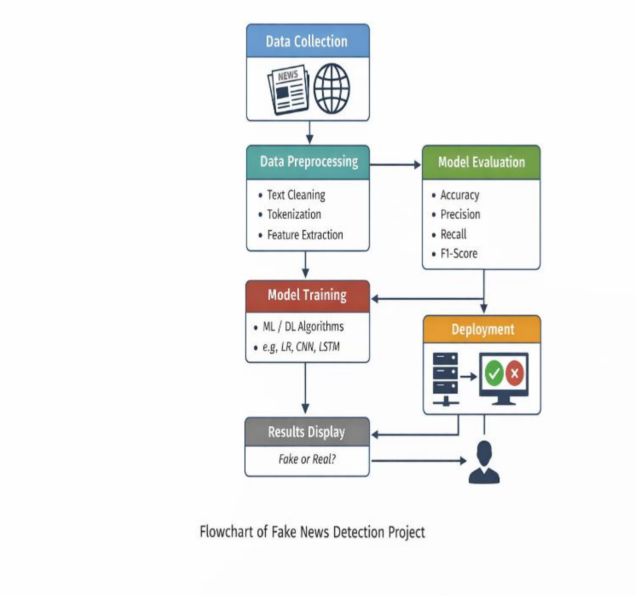
The proposed Multimodal Ensemble-Based Fake Media Detection Framework effectively identifies fake and AI-generated content across text, image, audio, and video modalities. By integrating ensemble majority voting and confidence aggregation, the system improves accuracy and reduces model bias compared to unimodal approaches. Experimental results confirm that multimodal fusion enhances robustness and reliability. Overall, the framework provides a scalable and practical solution for real-time media authentication and combating AI-generated misinformation. Furthermore, the modular architecture allows easy integration of advanced deep learning models as generative technologies evolve.

Appendix

This appendix provides additional technical details including implementation workflow and hyperparameter configuration.

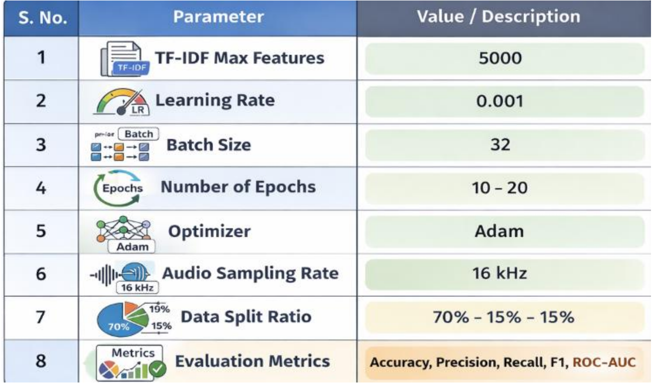
Fig. A1. Implementation workflow of the proposed multimodal detection framework.

A. System Implementation Workflow (Figure A1)



VI. B. Hyperparameter Configuration (Table A1)

Table A1 Model Hyperparameter Settings



S. No.	Parameter	Value / Description
1	TF-IDF Max Features	5000
2	Learning Rate	0.001
3	Batch Size	32
4	Number of Epochs	10 – 20
5	Optimizer	Adam
6	Audio Sampling Rate	16 kHz
7	Data Split Ratio	70% – 15% – 15%
8	Evaluation Metrics	Accuracy, Precision, Recall, F1, ROC-AUC

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this research work. The study was conducted independently without any financial, commercial, or personal relationships that could influence the results or interpretation of the findings.

Author Contributions

The authors contributed collectively to the development of this research work. The first author was responsible for conceptualization, methodology design, model implementation, experimentation, and manuscript drafting. The second author contributed to data collection, preprocessing, validation, and performance evaluation. All authors participated in result analysis, manuscript review, and final approval of the submitted version.

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