Advance Deception Detection

Humans' ability to detect lies is often no more accurate than chance. Traditional methods rely on human intuition or polygraph tests, which are less reliable. Recent advancements in AI, machine learning, and computer vision offer a more futuristic approach to deception detection. This paper presents a multimodal approach that combines text, video, image, and audio analysis to identify deceptive behavior, demonstrating that integrating multiple data sources can result in better accuracy.

by Swayam Singh, Krisha Patel, Priyanshi Airen

Introduction to Automated Deception Detection

The Challenge of Deception

Lying is an inherent part of human communication, present in various contexts from politics to personal interactions. While humans have an intuitive ability to detect deception, even experts are only slightly better than average at identifying lies.

The Rise of AI

Recent developments in Deep Learning and Computer Vision have opened new possibilities for identifying deception with greater accuracy. This has led to the development of automated deception detection, leveraging AI to analyze patterns in human characteristics.

This paper details the methodology, datasets, and implementation of a system using deep learning models and computer vision features. It integrates textual, visual, and auditory cues to analyze deception more comprehensively.

Literature Review: Integrating AI for Objectivity

Traditional Methods

Traditionally, experts analyzed speech patterns, facial expressions, and word choices to determine deception. However, human judgment can be subjective, making it prone to bias.

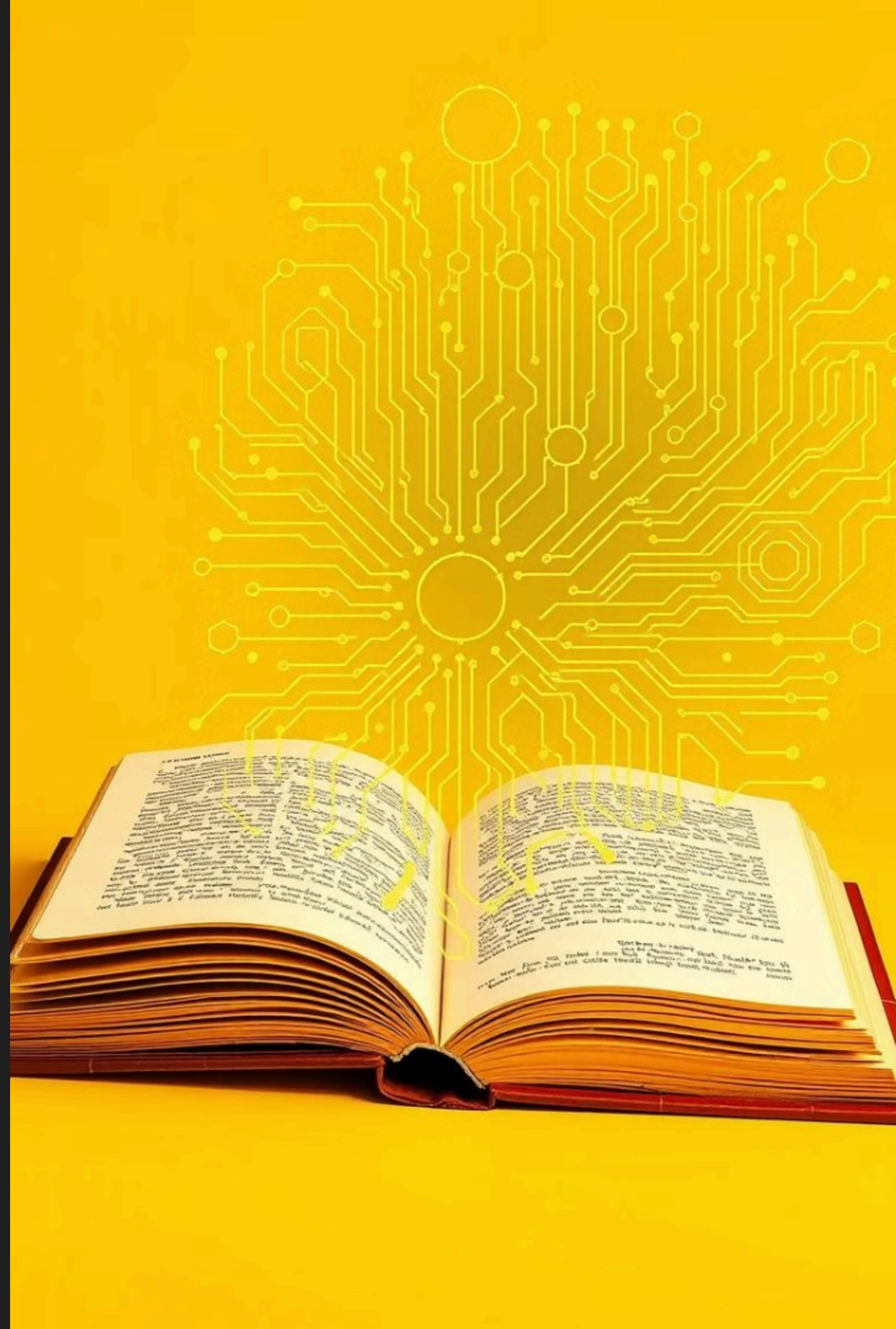
NLP Insights

Studies in Natural Language Processing (NLP) show that deceptive statements often contain fewer sensory details, indirect phrasing, and more justifications.

Multimodal Integration

Many existing models focus on only one modality at a time or fuse modalities post-detection, whereas our work integrates multiple modalities simultaneously and tests our model in real-time.

With current advancements in Deep Learning, researchers have started integrating AI to detect deception more objectively, making it more practical and adaptable for real-world applications.



Previous Work: Enhancing Accuracy with Multimodal Data

1

Single-Modal Methods

Previous research focused on single-modal methods by examining text, audio, or visual features separately.

2

Multi-Modal Integration

Studies shifted to multi-modal deception detection, integrating multiple data streams to improve accuracy.

3

Deep Learning Architectures

Recent work leverages deep learning architectures to process multimodal data more efficiently, helping achieve high accuracy in deception classification.

Our method builds upon these advancements but focuses on real-time multimodal deception detection, leveraging deep learning to process live textual, audio, and visual inputs for a practical and adaptable solution.

Methodology: Datasets for Training and Evaluation

Dolos Dataset

Contains 1,680 labeled video samples with multimodal behavioral and physiological features. Each statement is annotated with a binary value—truthful or deceptive—along with facial expressions, gaze patterns, and vocal behaviors.

Politifact Dataset

Consists of 11,188 statements containing claims by various individuals and organizations. Each statement is labeled with a binary value, where 0 represents false statements, and 1 represents true statements.

These datasets are used for training and evaluating deception detection systems, enabling the analysis of linguistic patterns and contextual information for deep learning applications.

Multimodal Analysis: Integrating Text, Speech, and Visual Cues

Text Analysis

TF-IDF vectorization and Bidirectional LSTM network to process textual data, enabling the model to understand past and future contexts.

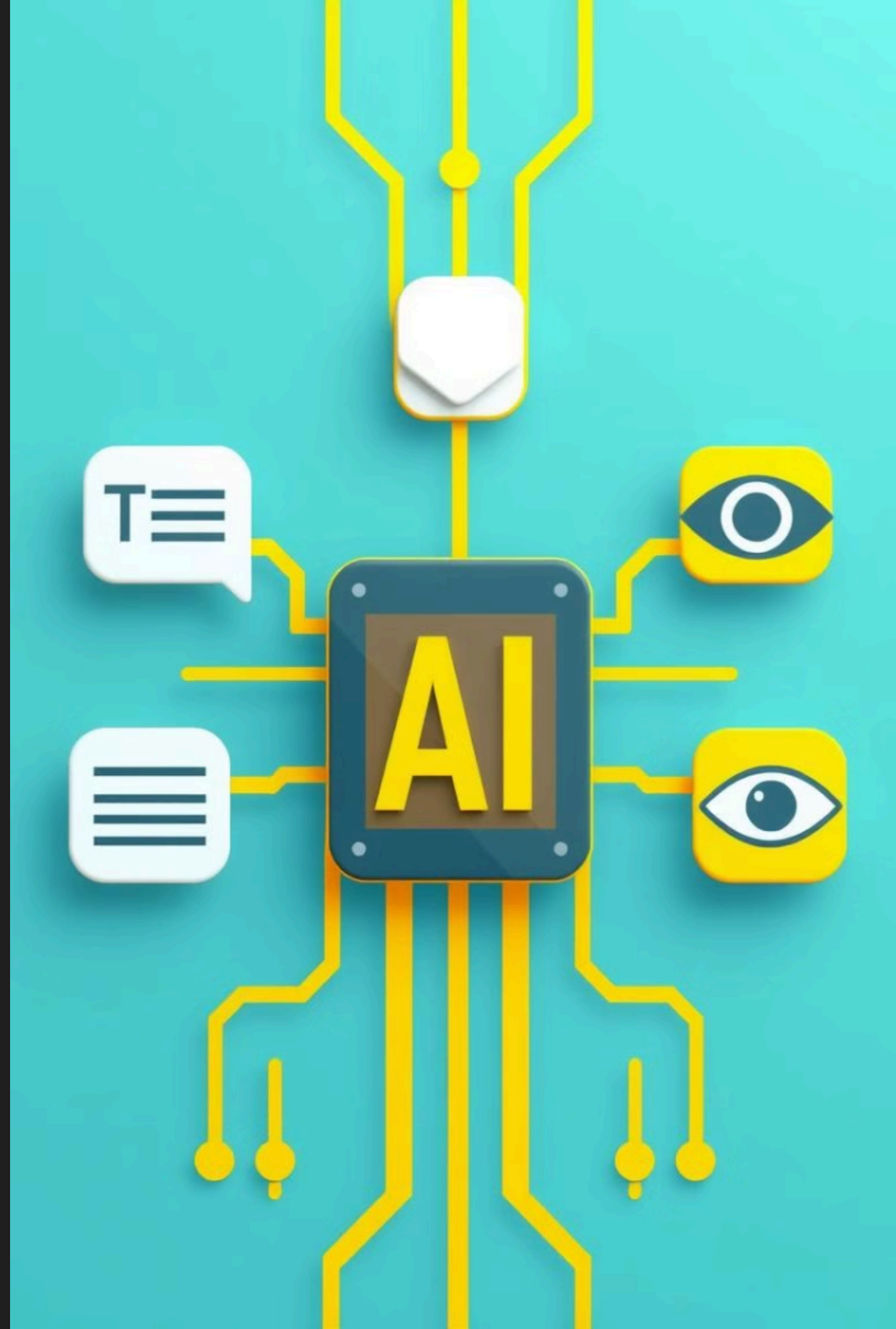
Speech Analysis

Audio capture system with PyAudio and a deep learning model trained on the Dolos dataset to detect fluency, pauses, pitch fluctuations, and tone variations.

Visual Analysis

Real-time detection using OpenCV, trained on the Dolos dataset to classify deception based on live camera input by capturing facial expressions and micro-expressions.

This approach focuses on real-time detection, integrating text, speech, and visual cues to develop a real-time AI model for deception detection.



Results and Conclusion: Real-Time Discrimination

Our methodology provides a sharp discrimination of truths and falsehoods, utilizing the textual, audio, and visual samples to conduct tests in real-time. By establishing a relationship of subgroups such as mouth movement and eye movement with real veracity, the model can sense how each subgroup influences the final veracity result.

This makes it more accurate in lie detection because it can pick up hand gestures, facial twitches, and many more finer features. The model can detect lies, but is not capable of detecting truths as best as possible, the deficiency here is because of less contextual information.

As a whole, we combined various modalities of data, written statements, heard cues, and bodily changes of face or hand all from original recorded data on a late night talk show based completely on lie detection.

Future Scope: Real-World Applications and Ethical Considerations

Law Enforcement

Detect deception in interrogations and minimize false positives and false negatives.

Cybersecurity

Catch remote identity fraud or deepfakes through behavior analysis.

Corporate Screening

Screen applicants for integrity and apply during high-risk transactions.

Ethical issues such as privacy protection and reducing bias will play a central role in ensuring an equitable and responsible AI deployment. By upgrading this model, and optimizing for real-time deception detection analysis, we are creating an AI tool that can redefine security, trust verification, and investigate techniques in multiple industries.

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