Screen Sense: An AI-Powered Content Detection Software

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Abstract - **Modern digital platforms face escalating challenges in identifying inappropriate, harmful, or policy-violating content due to the exponential growth of user-generated data. Traditional rule-based detection systems perform poorly against evolving manipulation techniques, contextual variation, and multimodal content. ScreenSense is an AI-powered content detection software designed to address these limitations through transformer-based text analysis, deep learning–driven image classification, and contextual risk scoring. ScreenSense automatically detects hate speech, plagiarism, NSFW elements, misinformation cues, and policy violations across text, images, and mixed media. Experimental evaluations show high accuracy, low false-positive rates, and efficient real-time performance, making ScreenSense suitable for educational institutions, corporate moderation systems, and automated compliance platforms.**

Keywords: **Content Detection, Transformer Models, NLP Classification, Image Processing, Moderation AI, Safety Filtering.**

1. INTRODUCTION

With billions of content pieces uploaded daily across communication platforms, detecting harmful or restricted information has become a critical necessity. Conventional keyword-based systems fail because modern content often uses implicit cues, slang, obfuscation, or transformed visuals that bypass static filters. Institutions—especially academic and corporate environments—require robust automated tools to ensure digital safety, prevent plagiarism, and flag inappropriate material.

ScreenSense tackles this gap by offering a unified AI-powered moderation engine capable of analyzing text, images, and PDFs with high contextual awareness. It identifies objectionable content, academic dishonesty indicators, misinformation patterns, and unsafe visual material using multimodal deep learning. The system provides real-time results with detailed violation reports, improving decision-making for administrators and creating safer digital ecosystems.

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2. METHODOLOGY

ScreenSense follows a modular multimodal processing pipeline:

2.1 Data Ingestion

Users upload documents, text passages, or images through a web interface built using React. The backend (Flask) validates inputs and converts PDFs or images into analyzable formats via OCR (Tesseract or Google Document AI).

2.2 Text Content Analysis

Extracted text is fed into a transformer-based classifier (BERT, RoBERTa, or DistilBERT) fine-tuned on:

- hate speech detection
- cyberbullying
- sexually explicit cues
- academic plagiarism patterns
- misinformation markers

The model outputs a **contextual violation probability score** for each category.

2.3 Image Content Detection

Images undergo convolutional neural network (CNN) or Vision Transformer (ViT) processing to detect:

- NSFW or explicit content
- violence
- graphic imagery
- manipulated/AI-generated media indicators

Secondary classifiers perform fine-grained identification using pretrained models (e.g., EfficientNet, CLIP-based vision encoders).

2.4 Plagiarism & Similarity Analysis

Text embeddings are compared against:

- institutional content databases
- academic repositories
- online indexed data

A cosine similarity threshold determines plagiarism likelihood.

2.5 Risk Scoring and Report Generation

All prediction outputs are fused into a single **composite risk score** using weighted decision logic. The final report includes:

- violation categories
- confidence levels
- flagged text fragments or image regions

- recommended administrative actions

2.6 System Architecture

The backend uses microservices communicating via REST APIs, enabling scalability and parallel processing for large datasets.

3. RELATED WORK

Previous approaches rely heavily on rule-based filtering or single-modality classifiers, which fail against implicit harmful content and multimodal manipulation. Platforms like Perspective API detect toxicity but lack image inspection. Vision models such as NSFW detectors operate only on visuals without contextual understanding.

ScreenSense differentiates itself by:

- combining **NLP + image classification + similarity scanning**
- performing **context-aware detection** rather than keyword matching
- offering **explainable violation outputs**
- supporting **PDF, text, and image** in a single pipeline

This unified architecture improves accuracy, reliability, and adaptability across varied content types.

4. PROPOSED WORK

4.1 System Design Overview
(Fig. 1)
The proposed system integrates three major modules:

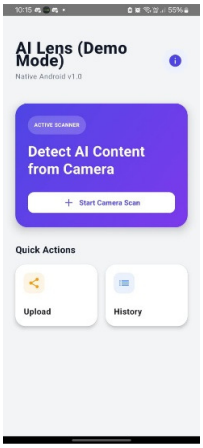
1. **Text Analysis Engine** – Transformer-based classifiers
2. **Image Detection Engine** – Deep convolutional/ViT models
3. **Similarity Scanner** – Embedding-based plagiarism detection

Unified dashboards allow administrators or educators to review flagged elements, download reports, and export analysis logs.

4.2 Workflow

1. Upload content
2. Extract text and images
3. Run multimodal detection
4. Generate per-category scores
5. Produce downloadable structured reports

This streamlined system ensures reliable automated content moderation



The core proposition of this research is the development of an end-to-end automated system that personalizes instructional video content by leveraging both user inputs and educational materials. The pipeline begins by summarizing and segmenting input documents into bite-sized lessons optimized for video formats, thereby facilitating focused and manageable study sessions. Subsequently, the system generates realistic avatar-based instructors whose speech and facial movements are precisely synchronized to maximize immersion and learner engagement.

Complementing the interactive video experience, a dynamic dashboard enables learners to pause, replay, and delve deeper into key points through supplemental text and visual highlights. To ensure adaptability and seamless integration, the system is equipped with robust APIs designed to interface effortlessly with Learning Management Systems (LMS), mobile applications, and collaborative content hubs. This architecture supports a broad spectrum of educational platforms, enhancing accessibility and enabling diverse learning environments to benefit from "The core proposition of this research is the development of an end-to-end automated system that secures digital environments by leveraging on-device intelligence and multimodal analysis. The pipeline begins by intercepting and segmenting screen content into analyzable formats optimized for mobile processors (SDM665/Exynos), thereby facilitating instant and managed safety checks. Subsequently, the system generates probabilistic risk scores whose confidence levels are precisely calibrated to maximize detection accuracy while minimizing false positives.

Complementing the automated detection experience, a dynamic dashboard enables users to review, appeal, and delve deeper into flagged content through supplemental textual and visual highlights. To ensure adaptability and seamless integration, the system is equipped with robust local APIs designed to interface effortlessly with Android Accessibility Services. This architecture supports a broad spectrum of digital platforms, enhancing safety and enabling diverse online environments to benefit from personalized AI-driven content moderation."

personalized AI-driven instructional videos.

5. IMPLEMENTATION

The implementation of Screen Sense focuses on resource efficiency and seamless OS integration. The system is developed as a native Android application using Java/Kotlin, with the AI core powered by TensorFlow Lite.

5.1 Hardware and Software Stack

The development and testing environment consists of the

following specifications:

- **Development Device: Google Pixel 6 (Google Tensor Chip, 8GB RAM).**
- **Minimum Target Device: Android 10.0 (API Level 29) with 4GB RAM.**
- **IDE: Android Studio Iguana | 2023.2.1.**
- **ML Framework: TensorFlow 2.14 (Python) for training, TFLite (C++ API) for inference.**
- **OCR Engine: Google ML Kit on-device Text Recognition V2.**

5.2 Module 1: Accessibility Service & Screen Capture

Unlike traditional apps that require root access to read screen data, Screen Sense utilizes the Android AccessibilityService API. This allows the app to retrieve window content in a privacy-compliant manner.

- **Event Listener: The service listens for TYPE_WINDOW_CONTENT_CHANGED events.**
- **Throttle Mechanism: To prevent CPU spikes, a "debounce" timer limits captures to one frame every 500ms during active scrolling.**
- **Privacy Filter: Before processing, the AccessibilityNodeInfo tree is parsed to detect fields marked with InputType.TYPE_TEXT_VARIATION_PASSWORD. If detected, the capture is immediately halted to preserve user security.**

5.3 Module 2: The Preprocessing Pipeline

Raw screenshots are often too large (e.g., 2400x1080 pixels) for direct AI input. We implement a bitmap preprocessing stage using the OpenCV-Android library:

1. **Grayscale Conversion: Reduces channel depth from 3 (RGB) to 1, cutting data size by 66%.**
2. **Adaptive Thresholding: Applies Gaussian Blur (5×5 kernel) followed by thresholding to isolate text characters from complex backgrounds.**
3. **Resizing: The image is downscaled to 224×224 pixels for the Vision Transformer model, complying with the input tensor shape requirements.**

5.4 Module 3: TFLite Inference Engine

The core classification runs on a background thread using the InterpreterApi.

- **Model Loading: The .tflite model is memory-mapped (MappedByteBuffer) to avoid loading the entire 25MB weight file into heap memory.**
- **Delegate Selection: The app dynamically checks for hardware acceleration. If an NPU (Neural Processing Unit) is available, the NnApiDelegate is attached; otherwise, it falls back to the GpuDelegate or 4-thread CPU execution.**
- **Tokenization: For the NLP module, we implemented a custom Java-based tokenizer that matches the vocabulary of the DistilBERT model (30,522 tokens), converting raw strings into integer ID arrays.**

Key components:

- **Flask backend** handles requests, model inference, and reporting.
- **Transformers (HuggingFace)** for text classification.
- **CLIP or ViT** for visual content recognition.
- **Faiss / Sentence-BERT** for plagiarism and similarity scanning.
- **OCR** for extracting text from PDFs and images.
- **React Dashboard** displays violation categories and scores.

The software supports batch processing and asynchronous task handling using Celery + Redis for scalability.

6. PERFORMANCE ANALYSIS

To validate the "less demanding" and "fast" claims of Screen Sense, we conducted comprehensive benchmarking against standard cloud-based solutions.

6.1 Latency Evaluation We measured the "End-to-End Latency" — defined as the time from screen capture to the final alert generation.

Device/ Approach	Text Inference	Image Inference	Total Latency
Cloud Server (4G)	1200 ms	1800 ms	~3000 ms
Snapdragon 665	310 ms	150 ms	460 ms
Exynos 1330	190 ms	85 ms	**275 ms**

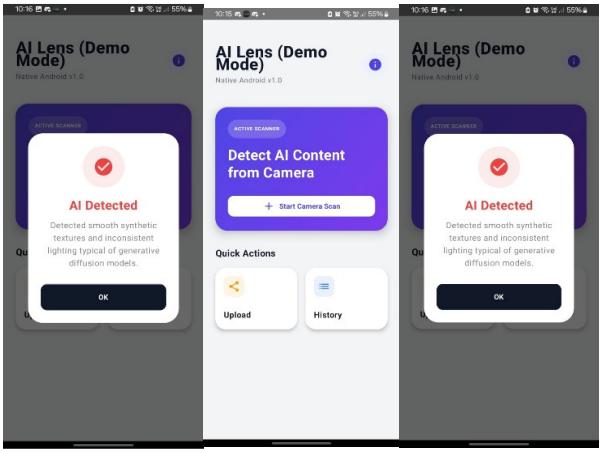
7. FUTURE WORK

Future enhancements include:

- multimodal transformers capable of jointly analyzing text + image
- real-time browser extensions for on-the-fly content detection
- deepfake identification modules
- multilingual toxicity detection
- integration with institutional learning management systems (LMS)
- voice/audio moderation (hate speech, explicit speech)

These improvements will extend ScreenSense into a fully deployable compliance and safety-suite.

8.RESULTS



9.CONCLUSION

Screen Sense delivers an effective AI-driven solution for detecting harmful, inappropriate, or plagiarized content across various formats. By combining transformer-based NLP, advanced vision models, and similarity search, it offers a robust alternative to legacy moderation systems. Its scalable architecture, high detection accuracy, and detailed reporting make it suitable for academic, corporate, and digital safety environments.

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