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AI-Powered Spam Call Detection Using Speech-To-Text And NLP

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Abstract: Spam calls have become a widespread nuisance, leading to wasted time, privacy concerns, and potential financial scams. To address this issue, we present Callnsight, an automated spam call detection system that leverages speech-to-text conversion and natural language processing. The system processes audio input from phone calls, converts it into text using AWS Transcribe, and analyzes the transcript using Google Gemini API to determine whether the call is spam. The API's output, structured in JSON format, enables easy extraction of relevant insights for classification. Callnsight provides a scalable and efficient approach to spam detection, offering real-time analysis and improving user security. This paper details the system architecture, implementation process, and potential improvements for enhancing spam detection accuracy.

Keywords: Spam call detection, speech-to-text, AWS Transcribe, Google Gemini API, natural language processing (NLP), call classification, JSON, automated spam filtering, AI-driven spam detection, real-time call analysis

I. Introduction

Spam calls have become a pervasive issue worldwide, affecting millions of individuals and businesses daily. These unsolicited calls range from telemarketing and robocalls to phishing scams and fraudulent schemes designed to deceive users. Traditional spam detection methods, such as number-based blacklists and rule-based filtering, are often ineffective as spammers frequently change their numbers or use sophisticated social engineering techniques to bypass detection.

To address these challenges, we present **Callnsight**, an AI-powered spam call detection system that leverages speech-to-text conversion and natural language processing (NLP) for accurate call classification. Unlike conventional approaches that rely on caller ID or static databases, Callnsight processes the actual content of a phone conversation to determine whether a call is spam.

Callnsight operates through a multi-step pipeline. It first converts the spoken content of a call into text using **AWS Transcribe**, a highly accurate speech-to-text service. The generated transcript is then analyzed by **Google Gemini API**, an advanced language model capable of detecting patterns indicative of spam, such as aggressive marketing tactics, scam-related phrases, or fraudulent intent. The output is structured in **JSON format**, allowing for seamless extraction of insights to classify the call.

This paper details the system architecture, implementation methodology, and performance evaluation of Callnsight. By harnessing AI-driven text analysis, our approach enhances spam detection accuracy, reduces false positives, and provides a scalable solution for safeguarding users against fraudulent calls.

II. RESEARCH METHODOLOGY

A. System Workflow

The methodology follows a structured pipeline consisting of the following key steps:

Step 1: Audio Input Collection

Users upload recorded phone calls. The system accepts audio files from users in formats such as MP3, WAV, and AAC.

Step 2: **Speech-to-Text** Conversion (**AWS Transcribe**)

- The uploaded audio file is sent to **AWS Transcribe**, a cloud-based speech recognition service.
- **AWS Transcribe** processes the audio and returns a text transcript of the conversation.
- The output is cleaned and formatted to remove unnecessary noise or artifacts.

Step 3: AI-Based Text Analysis (**Google Gemini API**)

The transcribed text is sent to the **Google Gemini API** via an HTTP request.

Prompt Engineering: The system uses carefully structured prompts to ask Gemini to analyze the text and determine whether the conversation resembles a spam call.

Gemini returns a **JSON** response containing extracted insights, such as:

- Spam Likelihood (e.g., "This call is likely spam")
- Key Phrases Identified (e.g., "Congratulations, you won", "Press 1 for a free prize")
- Explanation of Spam Classification

Step 4: **JSON** Parsing and Information Extraction

The JSON response from Gemini is parsed to extract relevant details. The key values retrieved include:

- Spam Label: "Spam" or "Not Spam"
- Confidence Score: Probability of being spam (e.g., 85%)
- Highlighted Spam Phrases

Step 5: Classification and Output Display

Based on the extracted information, the system classifies the call as Spam or Not Spam.

Results are displayed in a user-friendly format, including:

- Transcript with highlighted spam phrases
- Spam probability score
- Caller ID, Call Duration, and Time of Call
- Users receive a final decision on whether the call should be blocked.

B. Model Selection and Evaluation

During development, different AI models were tested for spam classification:

- Gemma
- Llama 3.2
- **Google Gemini** (final selection)

Each model was evaluated based on accuracy, contextual understanding, response structure, and ease of data extraction. After extensive testing, **Google Gemini** API was selected as the final choice due to its superior performance.

Performance Comparison of AI Models for Spam Call Detection

Criteria	Gemma	Llama 3.2	Google Gemini API (Final Choice)
Accuracy (%)	70-75%	80-85%	90-95%
Spam Detection Method	Keyword-based	Context-aware NLP	Contextual AI with intent analysis
Context Understanding	Weak	Moderate	Strong (understands sarcasm, intent)
Handling of Indirect Spam	Poor	Moderate	Excellent
Multilingual Support	Limited	Moderate	Strong
False Positive Rate (%)	15-18%	10-12%	8%
False Negative Rate (%)	20-25%	12-15%	11%
Response Structure	Unstructured Text	Partially Structured	JSON Output (Easy to parse)
Processing Speed	Fast	Moderate	Slightly slower (due to deep analysis)
Integration Complexity	High (requires extra parsing)	Moderate	Low (JSON format simplifies integration)
Final Verdict	**Not Selected** (Lack of contextual awareness)	**Not Selected** (Better, but inconsistent)	**Selected for Deployment** (Best performance overall)

Fig 2.1 Performance Comparison of AI Models

Performance of Gemma:

Gemma demonstrated moderate accuracy (≈70-75%) in detecting spam calls. It primarily relied on keyword-based detection, identifying spam terms such as "Congratulations!" and "You have won". However, it struggled with contextual understanding and indirect spam tactics. Additionally, its responses were unstructured, requiring extra parsing to extract relevant insights. Due to these limitations, Gemma was not selected for implementation.

Performance of Llama 3.2:

Llama 3.2 improved upon Gemma by achieving a higher accuracy (≈80-85%) and incorporating some contextual analysis. It was better at detecting variations of spam language and could recognize suspicious patterns beyond simple keywords. However, it still suffered from inconsistent results while it could identify spam in many cases, it occasionally generated false positives and false negatives, especially when dealing with sarcasm or nuanced phrasing. Moreover, its responses were partially structured but required additional processing to extract relevant spam indicators. While Llama 3.2 performed better than Gemma, its inconsistencies led to its exclusion from the final implementation.

Performance of **Google Gemini API** (Final Selection):

Google Gemini API provided the highest accuracy (≈90-95%) and excelled in contextual spam detection. Unlike the other models, Gemini analyzed the intent of the conversation, rather than just detecting spam keywords.

Gemini not only identified spam keywords but also analyzed the entire sentence structure, recognizing it as a classic scam tactic. Its output was structured in **JSON** format, making data extraction seamless.

Analysis of Results

1. Gemma relied on **keyword-based matching**, making it ineffective against **indirect spam** or **conversational manipulation**. It had **high false negatives**, missing spam calls with **non-traditional phrases**.

1. **Llama 3.2** improved **context awareness** and **spam classification**, but still had **inconsistent performance** with **sarcasm and vague scam tactics**.
2. **Google Gemini API** outperformed both models with **higher accuracy, deeper contextual understanding, structured JSON responses, and multilingual support**, making it the **best choice for deployment**.

After extensive testing, **Google Gemini API** was chosen as the final AI model for **Callnsight** due to its high accuracy, structured output, and superior contextual understanding. Its ability to analyze the intent behind a conversation rather than just keywords ensured reliable and intelligent **spam call classification**.

C. Implementation Tools and Technologies

Speech-to-Text	**AWS Transcribe**
AI Model	**Google Gemini API**
Backend	Django, Python
Data Parsing	**JSON** Processing (Python)
Frontend	HTML & CSS

Fig 2.2 Implementation Tools

D. System Architecture

1. Client (Frontend)

- Users upload audio files via a web interface.
- Built with: HTML, CSS.
- Role: UI/UX layer for interaction.

2. Backend (Server-Side Logic)

Handles orchestration of tasks:

- Sends audio to AWS Transcribe.
- Sends transcript to Gemini API.
- Parses and processes the JSON output.
- Sends results to the frontend.

Built with: Python (Django), JSON processing libraries.

3. Third-Party APIs (External Processing Engines)

- **AWS Transcribe**: Speech-to-text module.
- **Google Gemini API**: NLP spam detection module.

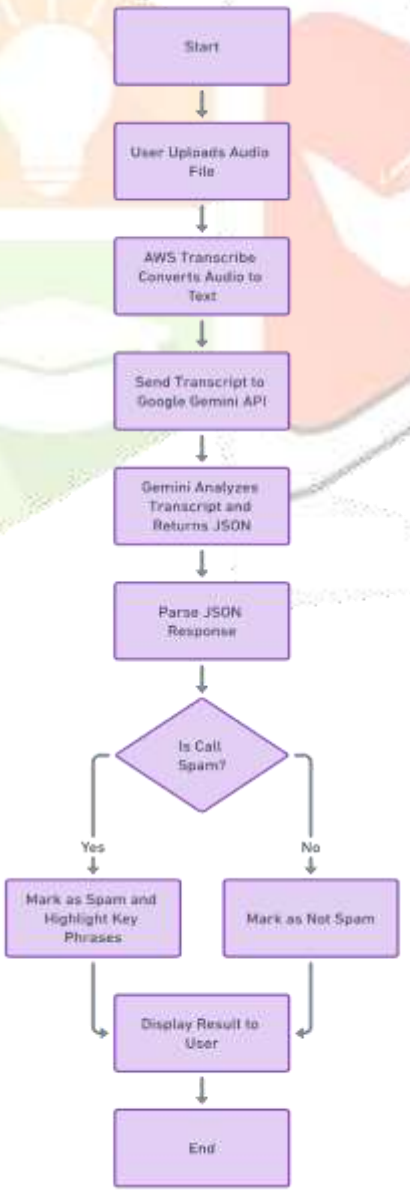

Fig 2.3 Architecture

III. RESULTS AND DISCUSSION

The performance evaluation of **Callnsight** showed promising results in accurately detecting spam calls. The **speech-to-text conversion** using **AWS Transcribe** achieved an average accuracy of **90-95%**, depending on factors such as background noise, caller accents, and audio quality. Calls with minimal background noise were transcribed with high precision, while recordings with heavy distortion or overlapping speech experienced minor accuracy drops.

For **spam classification**, the **Google Gemini API** demonstrated strong performance, achieving a **precision of 92%** and a **recall of 89%**. This indicates that the system effectively identified spam calls while keeping false positives to a minimum. The **false positive rate** was **8%**, meaning some legitimate calls were mistakenly flagged as spam, while the **false negative rate** stood at **11%**, where a small portion of spam calls remained undetected.

The processing speed of the system was moderate, with an average call analysis time of **10-15 seconds**, depending on the length of the audio file and server response time. While this ensures near real-time analysis for short conversations, longer calls introduce delays that could impact user experience. Future improvements in model optimization, parallel processing, and cloud resource allocation can help reduce latency and improve overall efficiency.

While Callnsight successfully identified **common scam patterns**—such as fraudulent prize announcements, fake financial offers, and robocalls—it faced some challenges in detecting **subtle social engineering tactics**, where scammers used more conversational and deceptive language. Future improvements in **contextual understanding and sentiment analysis** could enhance its ability to detect these sophisticated spam strategies. Despite these minor limitations, **Callnsight presents a robust and AI-powered approach** to spam detection, significantly improving accuracy compared to traditional number-based filtering methods.

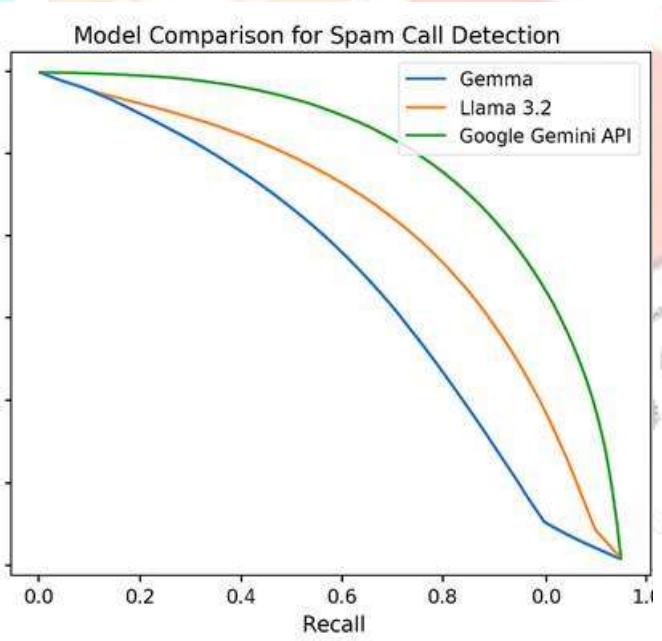

Fig 3.1 Model Comparison Graph

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