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Voice AI Risk Signaling: Using Home Assistant Devices to Detect Undeclared Property Hazards

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Abstract: With the increase in smart home adoption, voice-enabled devices like Amazon Alexa, Google Home, and Apple Siri are becoming increasingly abundant. Most of the new homes use these smart devices, and the old ones are upgrading to integrate these voice-enabled assistants. This paper explores a novel study for using voice data, with user consent, to identify the undeclared or non-reported risks within residential properties. By analyzing the speech using the natural language patterns, complaint frequency, and targeted keywords signals, we propose an Artificial Intelligence-based model to measure underlying risks that is not available in the traditional underwriting models has a very high potential to translate risk profiling dynamically, which will lead to improved pricing accuracy, fair pricing and diminish claim leakage in the property insurance.

Keywords: Voice AI, Property Insurance, Risk Detection, Smart Home, NLP, Underwriting, Risk Scoring, Digital Insurance, Behavioral Analytics, Privacy-Aware AI

1. Introduction

The whole property and casualty insurance industry is experiencing digital transformation by leveraging the IoT sensor data, Artificial intelligence models, and real-time dynamic data to enhance insurers' underwriting and the claim process. Though a critical loophole exists, which is underreported or unreported risks in the homes, like mold, plumbing issues, poor electricity infrastructure, etc. These issues frequently remain unnoticed till the time a claim is reported, which creates adverse selection and inefficient pricing. Most of the time, homeowners neglect these issues, imagining this is something that can be dealt with easily, but that's not the case. To fill this gap in the home insurance space, we introduced a novel concept in the paper on Voice AI risk signaling. The voice-enabled home assistant devices behave as passive risk identifiers through speech data analysis using natural language processing[1]. This paper aims to propose a new layer of proactivity and behavior-based underwriting.

2. Literature Review

The current smart home insurance workflow is fully dependent on the structured sensor data of the devices installed at the user's home. These sensors detect water leaks, smoke detection, and electrical wiring issues, which offer only binary or threshold-based insights. In contrast, human voice is enriched with context, emotions, and behavior patterns. Voice-based models have proved in mental health, elder care, and sentiment detection applications, but their potential use the home or property insurance has not been explored yet. Previous work has also discovered acoustic anomaly detection, such as glass break, fire alarms, but the elucidation of speech for insurance risk detection is an emerging field.

In a real-time use case, a murder case was solved by Alexa, in which a husband killed his wife and was jailed for 20 years. Voice recording on the Amazon Alexa helped bring the victim to justice. The detectives discovered that the voice records recorded by Alexa at the time of the murder helped them to solve the case. sounding 'out of breath' when saying 'Turn on - Alexa' during the early hours of the morning, when the murderer killed his wife. This shows how the speech was able to resolve the case; otherwise, it could have remained unnoticed. [2]

In another study, it is mentioned that the virtual assistants played a key role in solving a mystery case when voice recordings from an Amazon Echo device were used as evidence in a murder investigation. In the U.S. "Bates" case, police sought access to audio data captured by the device to uncover details about the crime, raising major legal and ethical questions. The case highlighted how virtual assistants, while designed for convenience, can also act as silent witnesses, potentially aiding law enforcement but also challenging privacy rights and data ownership[3].

Furthermore, Tabetha explained in his study about the legal and ethical ramifications, showing how the cloud-based recording can be an important evidence in detecting domestic violence used to solve the cases using the data. This helps the detectives in identifying the victims of abuse.[4] The voice is captured from the devices and is sent to the cloud, where it is stored.

Additionally, in a study, Kumar, Gupta, and Sapra explained that integrating Natural language processing to convert speech to text is effective. NLP captures the user's speech input and processes it into text based on vocal parameters like pitch, loudness, and intonation. They have calculated the application's performance using hidden Markov models, showing strong results with 91.5% precision, 95.4% recall, 86.8% F1 score, and 89% accuracy. This exposes that the text-to-speech conversion is accurate and captures the correct information.[5]

Lastly, in one of the studies, it was highlighted that while voice assistant awareness is high (90%) and usage is widespread (72%), most users still rely on them for basic tasks like playing music or checking the weather. Around 50% of people purchased these devices for their regular small work. However, trust remains the major challenge for most users, and this is the biggest challenge in voice commerce. [6]

Based on the above literature study, it is evident that the voice detected by the smart home devices is providing evidence in the mystery cases where no one can be able to trace the victim. The existing literature lacks the same use case in insurance, and that gap we are going to cover in this paper.

3. METHODOLOGY

- **Data Collection**:
  The user will be asked to opt for the data collection by the insurance company in return for a discount and fair pricing. With user opt-in, anonymized transcripts from the voice-enabled home assistant interactions are collected over a regular interval of time. These primarily include everyday conversations, queries, and complaints about the home. The speech-to-text workflow converts audio data into structured text for the analysis. The data will be stored on

the provider's cloud. Below is the Python code that can be utilized for the same.

```
import speech_recognition as sr

recognizer = sr.Recognizer()
with sr.AudioFile("sample_audio.wav") as source:
    audio = recognizer.record(source)
    transcript = recognizer.recognize_google(audio)
print(transcript)
```

Risk Signal Dictionary:

A curated set of keywords and phrases is developed through expert consultation and historical claims analysis. Examples include: "leaking pipe," "weird smell," "breaker tripped again," "can't sleep because of the cold," and "sparks came out." The below Python code shows how the keywords will be stored.

```
risk_keywords = ["leaking pipe", "weird smell", "sparks", "breaker tripped", "water dripping"]
def detect_risk_phrases(transcript):
return [phrase for phrase in risk_keywords if phrase in transcript.lower()]
```

Natural Language Processing (NLP):

The transformer-based models, such as BERT, RoBERTa are fine-tuned on labeled data to classify segments of speech as risk-related or neutral. These models would be able to identify the speech that is useful for the underwriting model. The multi-label classification techniques are used to handle overlapping issues, e.g., electrical & humidity. This classification helps in the segregation of the risk data. The tokenization is handled using WordPiece embedding with positional encoding, and finally, the training is performed using a weighted binary cross-entropy loss to mitigate label imbalance.

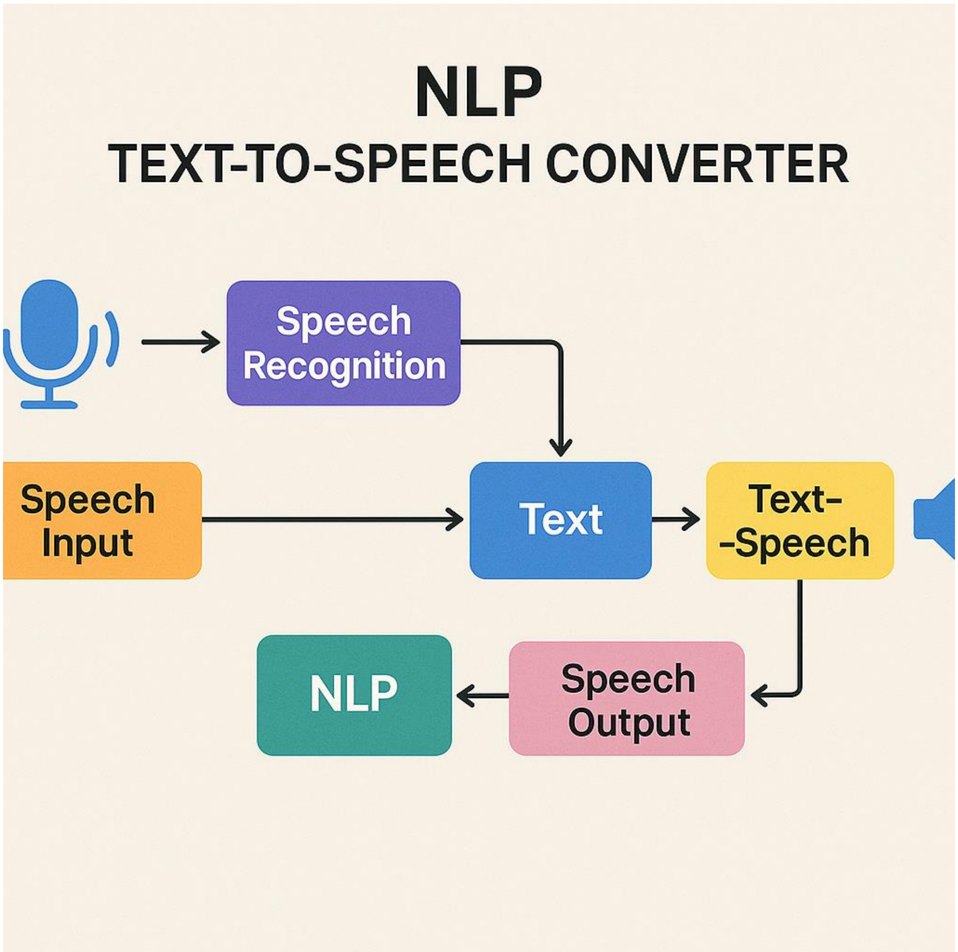

Fig. 1 NLP Text to Speech converter

Below is the Python code snippet for the same.

```
from transformers import BertTokenizer,
BertForSequenceClassification
import torch
tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
model=BertForSequenceClassification.from_pretrained("bert-base-uncased", num_labels=2)
inputs = tokenizer("There is a weird smell in the kitchen", return_tensors="pt")
outputs = model(**inputs)
predictions = torch.argmax(outputs.logits, dim=-1)
```

Temporal and Sentiment Analysis:

The risk-related remarks or comments are analyzed over time for frequency, intensity, and sentiment polarity. An increase in urgency or negativity may indicate deteriorating home property conditions, which are very sensitive. A sliding window approach with exponential decay weights recent expressions more heavily in the underwriting scoring models. Below is the Python code snippet for the same.

```
from vaderSentiment.vaderSentiment import
SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
score = analyzer.polarity_scores("I'm tired of the dripping noise every night")
print(score)
```

Risk Scoring Engine:

The homeowners will receive a composite risk score derived from the volume, severity, and diversity of detected issues at home, adjusted for demographic and geographic factors. The score is updated weekly, using a dynamic rolling average to stabilize transient anomalies. Below is the Python code snippet for the same.

```
def calculate_risk_score(phrases_detected,
sentiment_scores, time_decay=0.85):
    base_score = len(phrases_detected) * 10
    sentiment_modifier = -
sentiment_scores['compound'] * 5
    adjusted_score = (base_score + sentiment_modifier)
* time_decay
    return round(adjusted_score, 2)
```

4. Case Study Simulation

We have generated a synthetic dataset of 10,000 voice assistant transcripts using the generative language models, as real-time data requires a lot of privacy and safety considerations. We are incorporating both benign and hazard-related content. Data augmentation techniques like back translation and contextual synonym replacement ensured linguistic variability. A fine-tuned BERT model achieved:

- Risk classification accuracy: 92.3%
- Precision: 89.7%, Recall: 93.8%
- Early warning detection: Identified 78% of emerging risks at least 3.2 months before physical inspection or sensor triggers.

An example insight: A simulated household showed recurring complaints about "damp smell in the basement" and "water dripping noise" weeks before a major water damage claim. The model successfully flagged this as a high-risk case.

5. Ethical and Privacy Considerations

This proposed framework highlights full user transparency and ethical AI design. Key principles include:

- **Opt-in Consent**: Users must explicitly agree to share voice data for insurance analysis for the insurer. They will get a document for their consent approval.
- **Data Anonymization**: Personal identifiers are stripped from transcripts before model processing to make sure privacy is maintained.
- **Right to Opt-Out and Erasure**: Users can revoke consent or request data deletion at any time if they feel uncomfortable or useless. For those customers, the traditional method will be used to rate the policy, and they will give up their discount.

- **Transparency and Disclosure**: Insurers must disclose how data will be used and not used, e.g., not for automatic premium hikes without review. The report should be shared with the insured on what basis they think the premium should go up.
- **Compliance**: This proposed framework will adhere to GDPR, CCPA, and NAIC model privacy regulations.

6. POTENTIAL APPLICATIONS

- **Dynamic Underwriting**: The Traditional risk models are updated periodically based on the claims recorded or insurance factor increase, but the voice-based models offer dynamic underwriting and adaptive pricing.
- **Proactive Risk Mitigation**: Regular alerts and recommendations can be sent to insureds based on voice-detected issues, e.g., "Consider inspecting your HVAC system", "Check your kitchen plumbing".
- **Claims Validation**: The Claims adjusters can verify whether the issue was previously captured, helping them reduce fraud and expedite payouts.
- **Customer Segmentation**: Behavioral data may expose proactive versus reactive homeowners, filtering engagement strategies.

7. LIMITATIONS AND FUTURE WORK

This is a conceptual model and has not yet been implemented in a real-world insurance product. Challenges include:

- **Data Access**: Acquisition of consent from home smart device users for real-world pilot studies is a challenge, as people might see this as a threat to their privacy.
- **Bias and Misclassification**: A need to address fairness and prevent overfitting on certain demographic or linguistic groups. Every language must be carefully verified.
- **Multimodal Fusion**: Future iterations of this model should integrate voice data with visual (CCTV), environmental (sensors), and geospatial data for complete risk modeling.
- **Federated Learning Potential**: Future work could implement privacy-preserving model training directly on edge devices.
- **Regulatory Hurdles**: Insurance regulators will need clear frameworks on the acceptable use of unstructured data and what can't be translated.

8. CONCLUSION

Voice AI Risk Signaling heads a revolutionary direction in property insurance. Capturing the undeclared factors of home maintenance and upcoming issues through natural language processing, insurers gain a new parameter for their insurance model to rate the policies. By following the privacy rules and regulations, ethical usage, this model promises to improve the safety, trust, fairness, and actuarial accuracy. Future developments can further implement this architecture into the smart insurance workflow.

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