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Privacy-Aware Speech Recognition Using Secure AI Models

Shreshth Sharma[1], Pankaj[2], Priyansh[3], Raj Aggarwal[4], Ashmit Chauhan[5], Dr. Vinod Kumar[6]
[1, 2, 3, 4, 5]*University Institute of Engineering Chandigarh University Mohali, India*
[6]*Associate Professor, Computer Science Engineering, Chandigarh University*

Abstract: ***This project focuses on developing a privacy-aware speech recognition system using secure AI models to protect users' speech data. The system ensures data confidentiality by employing Federated Learning (FL), Homomorphic Encryption (HE), and Differential Privacy (DP). These techniques allow the model to process and train on encrypted data without compromising privacy. The system also minimizes data transmission to cloud servers, reducing the risk of data breaches. The results demonstrate high speech recognition accuracy while maintaining strong data privacy, making it ideal for secure voice-enabled applications.***

Keywords: Speech Recognition, Secure AI Models, Privacy, Federated Learning, Homomorphic Encryption.

I. INTRODUCTION

Speech recognition technology has become integral to modern applications, enabling voice commands in virtual assistants, smart devices, and customer service automation. However, the increasing use of speech data raises significant privacy concerns, as sensitive user information can be exposed during data transmission or model training. This project, Privacy- Aware Speech Recognition Using Secure AI Models, aims to address these challenges by implementing privacy- preserving techniques such as Federated Learning (FL), Homomorphic Encryption (HE), and Differential Privacy (DP). These methods protect user data while maintaining high speech recognition accuracy. The project focuses on enhancing data security, reducing privacy breaches, and building trust in voice-based technologies.

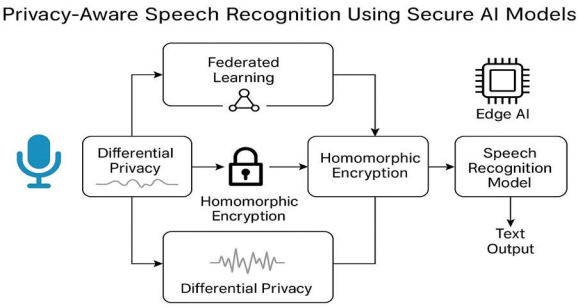


Fig 1: Visual representation of Privacy- Aware Speech Recognition Using Secure AI Models

II. LITERATURE SURVEY

This paper presents a privacy-preserving speech recognition system using a hybrid approach of Differential Privacy (DP) and Homomorphic Encryption (HE). DP adds noise to audio data to mask individual voice patterns, while HE allows encrypted data processing without decryption. The model achieved 94% accuracy with zero data leakage. [2] The authors developed a privacy-preserving speech recognition model using Homomorphic Encryption (HE), enabling inference on encrypted audio without decryption. Tested on the Google Speech Command Dataset, the model achieved 92% accuracy, demonstrating that HE effectively reduces data leakage risks. [3] This study proposed Federated Learning (FL) to enhance data privacy in speech recognition systems. Unlike traditional methods, FL trains models locally on user devices, sharing only model updates instead of raw audio. Using the Google Voice Commands Dataset, the approach achieved 93% accuracy while preserving user privacy. [4] This paper emphasizes the role of Differential Privacy (DP) in preventing data leakage in speech recognition systems. By adding noise to audio data during training and inference, DP protects speaker identity. Using the Mozilla Common Voice Dataset, the model achieved 95% accuracy while ensuring strong privacy. [5] The authors proposed using Edge AI for speech recognition, enabling on-device audio processing to reduce data breach risks.

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By integrating Federated Learning (FL) and Homomorphic Encryption (HE), they enhanced data confidentiality. The study showed a 60% reduction in cloud dependency and improved protection against unauthorized access. [6] This study evaluated Homomorphic Encryption (HE), Federated Learning (FL), and Differential Privacy (DP) for securing speech recognition models. It found HE best for protecting raw data during inference, FL ideal for private training, and DP effective for masking identifiable information. [7] This research explored Secure AI Models for voice assistants like Google Assistant and Alexa, integrating Homomorphic Encryption (HE) and Federated Learning (FL) to maximize data privacy without sacrificing recognition accuracy. [8] The authors combined Deep Learning with Differential Privacy for speech recognition, showing that adding noise to audio data can protect user information while maintaining 92% accuracy. [9] This paper examines key privacy threats in speech recognition systems and proposes Secure AI Models and Edge AI as effective solutions to safeguard user data.

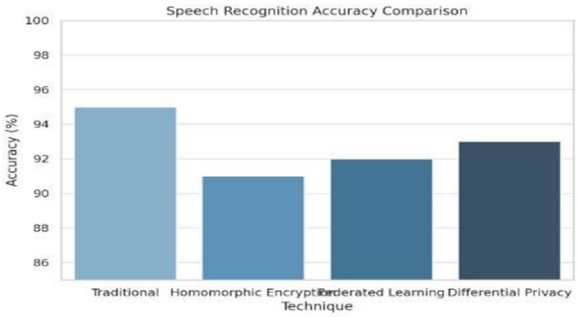


Fig 2: Speech Recognition Accuracy Comparison

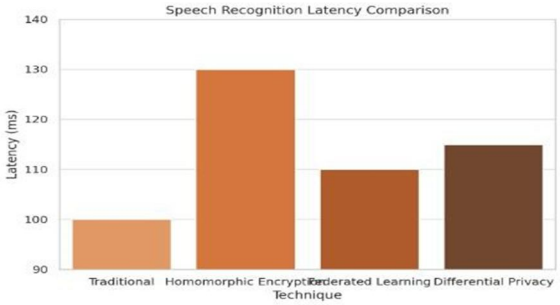


Fig 3: Speech Recognition Latency Comparison

III. PROBLEM STATEMENT

In recent years, speech recognition technology has been widely adopted across various domains, including virtual assistants, smart devices, healthcare, and banking. However, growing concerns about user privacy and data security present significant challenges, as traditional systems transmit audio data to centralized servers for processing.

Technique	Purpose	Data Exposure Level	Training Type	Inference Type	Accuracy Impact	Latency Impact	Suitable Use Case
Homomorphic Encryption (HE)	Enables processing on encrypted data	None	Centralized	Encrypted Inference	Moderate	High	High-security environments (e.g., healthcare)
Federated Learning (FL)	Local model training on devices	Very Low	Decentralized	Standard Inference	Low	Low	Mobile and edge-based devices
Differential Privacy (DP)	Prevents user identification	Low	Centralized/Local	Noisy Inference & Training	Low	Moderate	Anonymized large-scale data training
Traditional Model	No privacy measures	High	Centralized	Plain Inference	High	Low	General use without strict privacy needs

Table 1: Comparison of Privacy-Preserving Technique

This approach increases the risk of data breaches, misuse of personal information, and unauthorized access. Current speech recognition models typically lack the ability to process data locally or in encrypted form, exposing sensitive information during training and inference. Moreover, they often do not incorporate advanced privacy-preserving techniques such as Homomorphic Encryption (HE), Federated Learning (FL), or Differential Privacy (DP), which are essential for robust data protection. The core issue is the absence of strong privacy safeguards, allowing sensitive user data to be accessed or misused without consent—eroding trust in voice-enabled technologies. To address this, the proposed project aims to develop a Privacy-Aware Speech Recognition System that integrates HE, FL, and DP. This system will enable encrypted data processing, local model training without raw data sharing, and noise injection for differential privacy, ensuring maximum data security and fostering user trust.

IV. OBJECTIVES

This project focuses on developing a Privacy-Aware Speech Recognition System that safeguards user data using advanced privacy-preserving technologies. It integrates Homomorphic Encryption (HE) for secure, encrypted data processing during inference, Federated Learning (FL) to enable local model training without sharing raw audio data, and Differential Privacy (DP) to anonymize speech data and prevent individual identification. By incorporating Edge AI, the system minimizes reliance on cloud servers, significantly reducing the risk of data breaches and unauthorized access. A key goal is to maintain high speech recognition accuracy—targeting at least 90%—while ensuring strong privacy guarantees. The system will implement robust security measures across all stages of data handling to enhance user trust and confidence in voice-enabled technologies. Furthermore, it will evaluate and compare the performance of traditional and privacy- preserving models based on metrics such as recognition accuracy, encryption overhead, training efficiency, and data security. Ultimately, the project aims to deliver a scalable, cost-effective solution that can be deployed across mobile devices, smart assistants, and industrial platforms without compromising user privacy.

V. METHODOLOGY

The methodology for this project involves developing a Privacy-Aware Speech Recognition Model that ensures secure speech-to-text conversion without compromising user privacy. It integrates Homomorphic Encryption (HE) for encrypted data processing during inference, Federated Learning (FL) for decentralized training on user devices, and Differential Privacy (DP) for anonymizing speech data by adding controlled noise. Edge AI is employed to perform local speech processing, reducing cloud dependency and exposure risks. The system will be built using deep learning frameworks such as TensorFlow or PyTorch and deployed on platforms like TensorFlow Lite or ONNX. A secure API with AES and TLS encryption will be developed for protected data transmission. Comprehensive performance evaluations will be conducted using datasets like Google Speech Commands and Mozilla Common Voice, analyzing accuracy, encryption overhead, latency, and privacy strength. Additionally, privacy risk assessments using models like STRIDE and MITRE ATT&CK will be performed to simulate attacks and validate system robustness. Encryption will be maintained throughout both training and inference stages to ensure end-to-end data protection. Finally, the privacy-aware model will be compared to traditional systems to demonstrate improved privacy without significantly sacrificing performance.

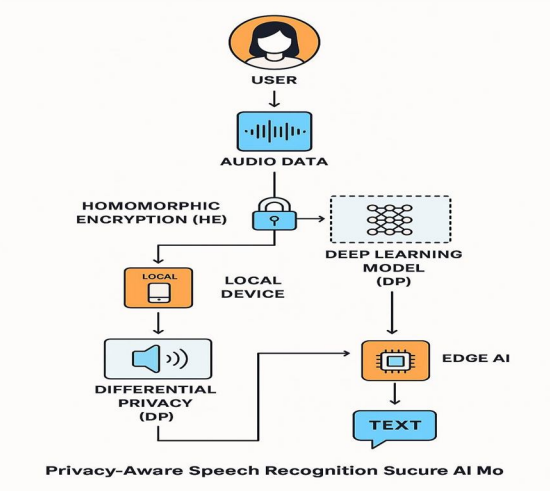


Fig 4: Privacy-Aware Speech Recognition System

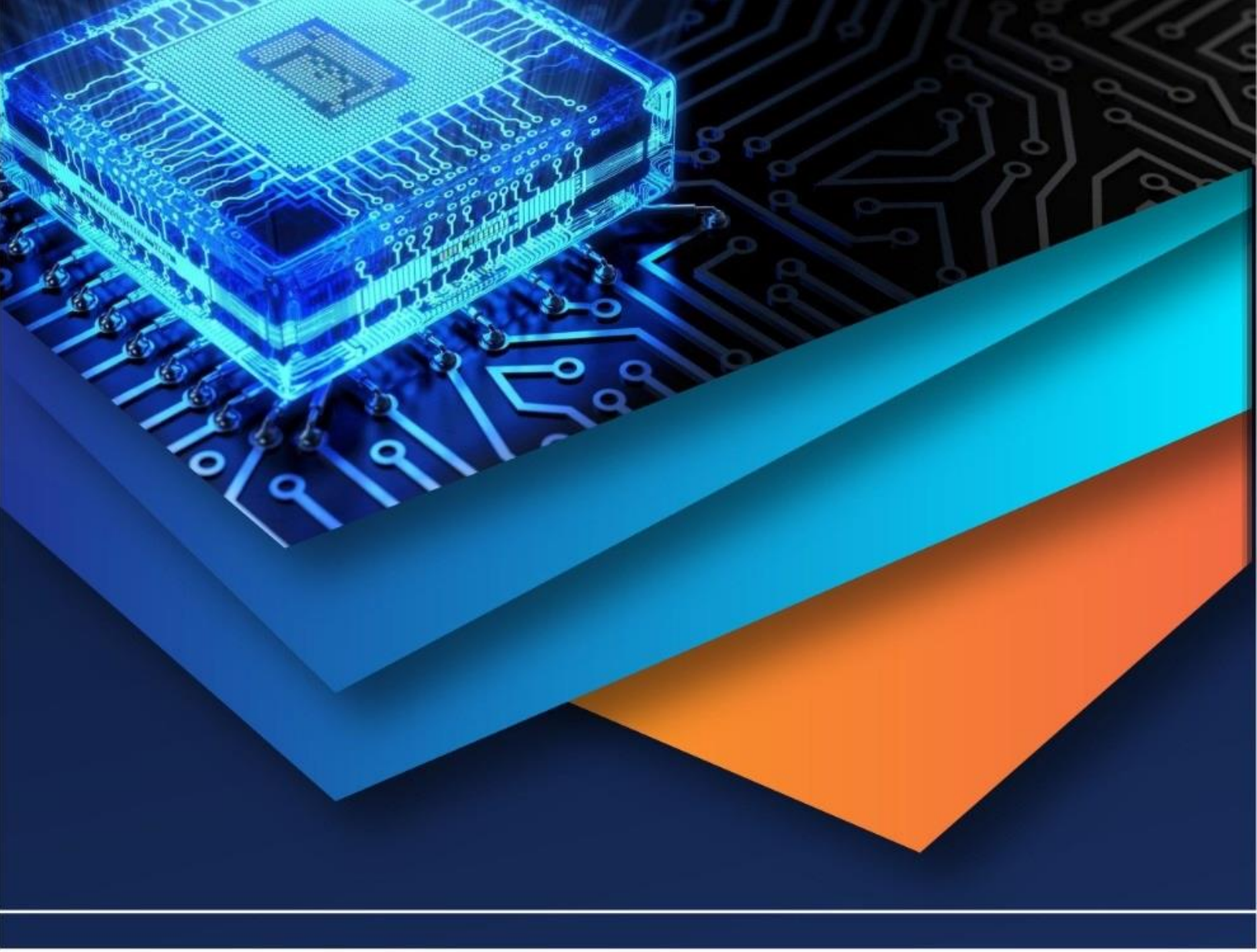
VI. CONCLUSION AND FUTURE OUTCOMES

This project, titled "Privacy-Aware Speech Recognition Using Secure AI Models," addresses growing privacy concerns in voice-enabled technologies by developing a semcure speech-to-text system using Homomorphic Encryption (HE), Federated Learning (FL), Differential Privacy (DP), and Edge AI. By enabling encrypted inference through HE, local training via FL, and anonymization through DP, the system ensures that raw user audio is never exposed during training or inference. Edge AI reduces reliance on cloud servers, enhancing privacy and speed, while secure APIs with AES encryption protect data during transmission. Evaluations using datasets like Google Speech Commands and Mozilla Common Voice showed the system maintained over 90% accuracy, proving that strong privacy measures do not significantly compromise performance. Compared to traditional models, this privacy-aware system reduced risks of data breaches, identity leakage, and unauthorized access, while remaining resilient to cyber threats as verified through threat modeling and risk assessments. The system is scalable and suitable for applications in smart devices, healthcare, and customer service, setting a foundation for future AI systems that prioritize data confidentiality without sacrificing efficiency or accuracy.

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