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MEMLOG – Multisensory Life Logging with AI-Powered Insights

Enhancing Memory, Behavior Tracking, and Cognitive Support Through Wearable Technology

Presented by:
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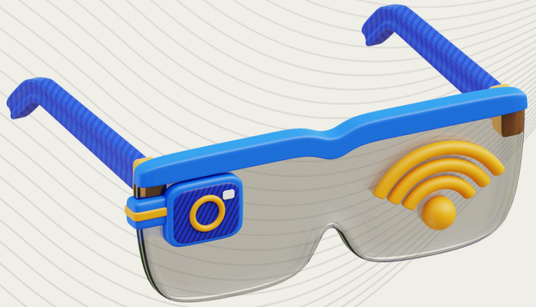

Agenda

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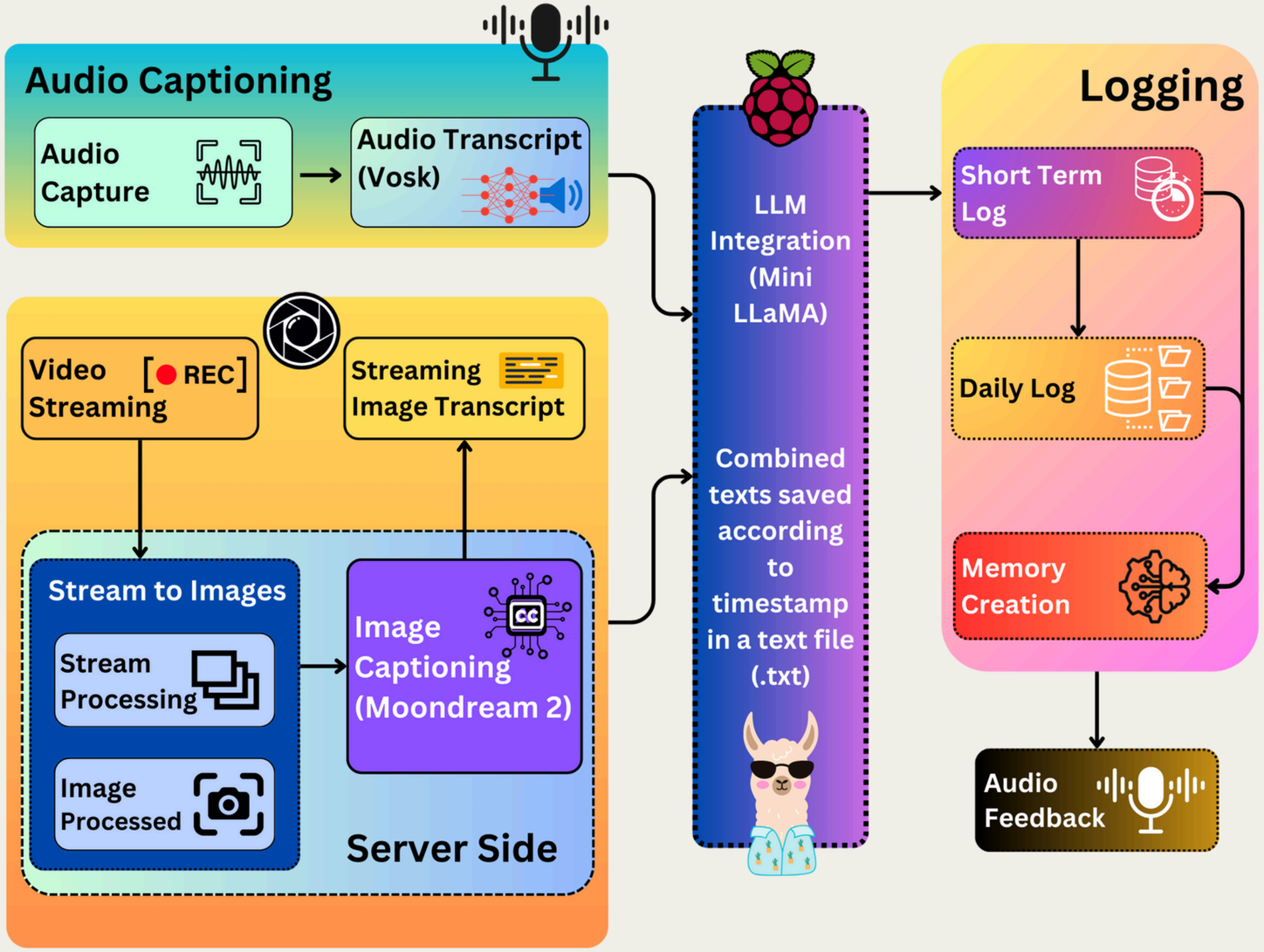
- **Introduction:** Overview of MEMLOG concept and objectives
- **Problem Statement:** Addressing memory gaps and cognitive challenges
- **Data & Approach:** Capturing, preprocessing, and summarizing multisensory data
- **Modeling & Experiments:** Supervised classification, unsupervised clustering, and evaluated models
- **Results & Insights:** Key findings, improvements, and user benefits
- **Conclusion:** Final takeaways and reflections

Planned DataFlow



- **Audio Captioning:** Capture, transcription (Vosk), and processing.
- **Video Streaming:** Image extraction and captioning (Moondream 2).
- **LLM Integration:** Combines transcripts into timestamped logs.
- **Logging:** Short-term, daily logs, memory creation, and audio feedback.

Problem Statement

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- **Core Issue:** Many individuals struggle to retain and recall the details of daily interactions, conversations, and activities. This memory gap can stem from cognitive conditions (e.g., Alzheimer's, dementia) or from fast-paced lifestyles where crucial details slip through the cracks.

- **Cognitive Challenges:** Conventional memory aids often fail to offer real-time, context-aware support. Users need an unobtrusive system that captures experiences as they happen, ensuring important moments are not lost.

- **User Needs:**
  - Alzheimer's/Dementia Patients: Require tools to reinforce memory and autonomy.
  - Busy Professionals: Need a quick reference to past meetings, key points, and decisions.

- **Privacy Concern:** Existing solutions sometimes store raw data, risking user privacy. A privacy-first approach is essential.

- **Goal:** Provide a wearable, AI-driven system that generates concise, text-based event logs, allowing users to later query and retrieve meaningful summaries easily.

Data Description

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Multimodal Inputs:

- **Visual:** High-resolution camera embedded in smart glasses captures scenes. Data processed by Moondream 2 (Vision-Language Model) for object and context detection.
- **Audio:** Microphone input transcribed by Vosk speech-to-text engine. Offline capability ensures quick, private, and accurate transcripts.
- **Motion:** IMU sensors detect user movements & gestures, enriching context of activities or interactions.

Processing Pipeline:

- **Capture:** Glasses record visual frames, audio streams, and motion readings in real-time.
- **Preprocessing:** Visual data converted into text-based captions (no images stored), audio transcribed into text logs, motion data summarized into movement patterns.
- **Privacy Preservation:** Only summarized textual events are stored, never raw images or audio.

Tools & Frameworks:

- Moondream 2 for image captioning
- Vosk for speech-to-text
- Scripts for sensor data normalization and timestamp alignment

Research Questions

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Refined SMART Questions:

1. **Accuracy of Event Detection:** How accurately can the system identify and summarize significant events, conversations, or noteworthy interactions from multimodal inputs?
2. **Relevance of Summaries:** Can the system produce concise, context-rich text logs that enable meaningful recall without overwhelming the user with unnecessary details?
3. **Privacy & Efficiency:** Can event summaries be generated locally, minimizing reliance on external servers, while maintaining near real-time processing speed and user confidentiality?
4. **Cognitive Support Effectiveness:** Does the solution help users with memory challenges (e.g., Alzheimer's patients) by providing timely cues and structured recollections to improve daily functioning?

Goal Alignment: These questions guide the evaluation of model performance, usability, and privacy safeguards, ensuring that MEMLOG provides both practical value and ethical data handling.

Exploratory Data Analysis

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Initial Steps:

- Inspected raw captures from camera and microphone feeds before any summaries.
- Removed corrupted image frames and incomplete audio transcripts.
- Ensured consistent timestamp formats for synchronized multimodal analysis.

Descriptive Statistics:

- Identified frequently detected objects (e.g., “person,” “notebook,” “meeting room”) indicating commonly encountered contexts.
- Analyzed speech-to-text transcripts for average word counts, top keywords, and sentiment indicators to understand conversational flow.

Missing Values & Cleaning:

- Filled missing transcriptions with “UNKNOWN” tags.
- Dropped unusable corrupted data (~2%) to maintain reliability.

Key Insights:

- Certain periods of the day yield richer event logs (e.g., office hours).
- Emotional tone and object frequency patterns emerged, hinting at potential importance for event significance scoring.

Models Evaluated

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- **Moondream 2 (Visual):** Efficient vision-language model providing quick, context-aware image captioning. Pros: Lightweight, good accuracy on objects; Cons: Limited reasoning depth.
- **Wav2Vec 2.0 (Audio):** Robust speech-to-text model converting audio streams into transcripts. Pros: Accurate and relatively efficient; Cons: Slightly more demanding than Vosk.
- **Mini LLaMA (Text Summarization):** On-device LLM attempted for generating concise event summaries. Pros: Small footprint; Cons: Struggled under continuous load.
- **Mistral (LLM Tried):** High-performance LLM tested briefly. Pros: Advanced reasoning; Cons: Too resource-heavy for on-device use, caused frequent crashes.
- **BTLM-3B-8K (Server-Side):** Server-based LLM offering complex reasoning. Pros: More powerful summarization; Cons: Privacy risks, latency, required data transfer.
- **MiniGPT-4 (Edge):** Balanced approach for multimodal summarization at the edge. Pros: Better than Mini LLaMA in handling visual-text combos efficiently; Cons: Still resource-sensitive, but manageable with careful optimization.

Comparison of Image Captioning Models

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Model	Parameters	Performance	Resource Efficiency	Use Case
Moondream 2	1.86B	Basic tasks, limited reasoning	Efficient for laptops with GPUs like RTX 3060	Best for lightweight tasks on mid-range hardware due to low resource consumption.
LLaVA	13B	Complex reasoning, high accuracy	Higher resource requirements	Ideal for advanced applications requiring high accuracy, but resource-heavy.
MiniGPT-4	4B	Good balance of efficiency & performance	Mid-range resource needs	Great for tasks needing balance between performance and efficiency, but still demanding.
BLIP-2	12B	Accurate for vision-language tasks	Moderately resource-intensive	Excels at image captioning and visual QA but requires more resources than Moondream.
YOLOv8	-	High performance for object detection	Resource-efficient for visual tasks	Best for fast, accurate object detection, but lacks multimodal capabilities like text integration.

What Worked & What Didn’t

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Successes:

- **Vosk (Audio):** Provided reliable offline speech-to-text conversion. It was lightweight, accurate for diverse accents, and didn’t demand cloud connectivity.
- **Moondream 2 (Visual):** Delivered efficient object detection and scene captioning on-device, ensuring fast, context-rich outputs without heavy GPU requirements.

Failures & Challenges:

- **Resource-Intensive LLMs (Mistral, BTLM-3B-8K):** Although promising in capability, these models drained computational resources, introduced latency, and raised privacy concerns by requiring cloud processing.
- **On-Device Summarization with Larger Models:** Mini LLaMA broke down under continuous load, causing performance issues and overheating.

Key Takeaway:

- Achieving a balance between performance and privacy was crucial. Lightweight, on-device solutions (Vosk, Moondream 2) were practical, while heavier LLMs or server-based approaches fell short due to resource constraints and privacy risks.

LLM Comparisions

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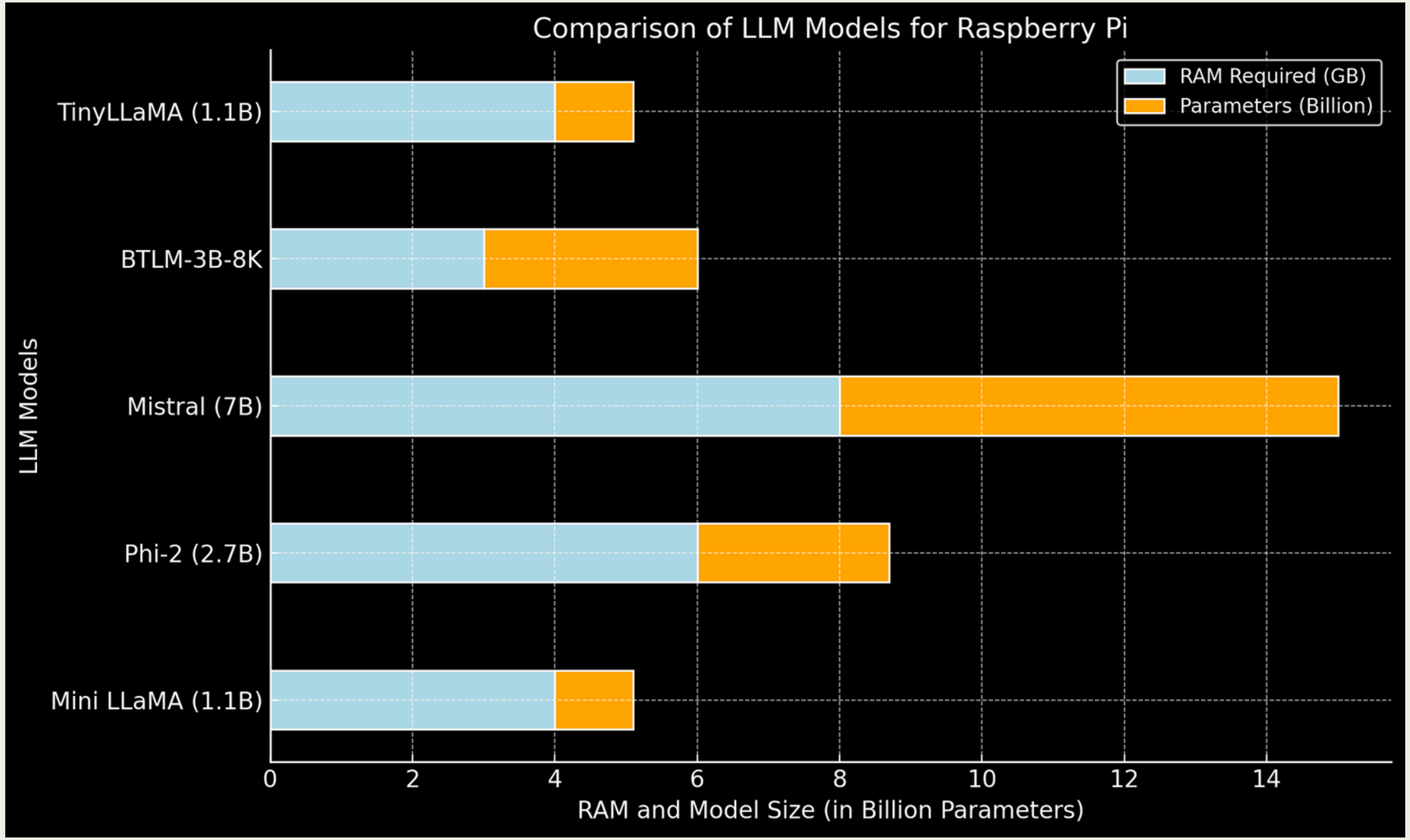
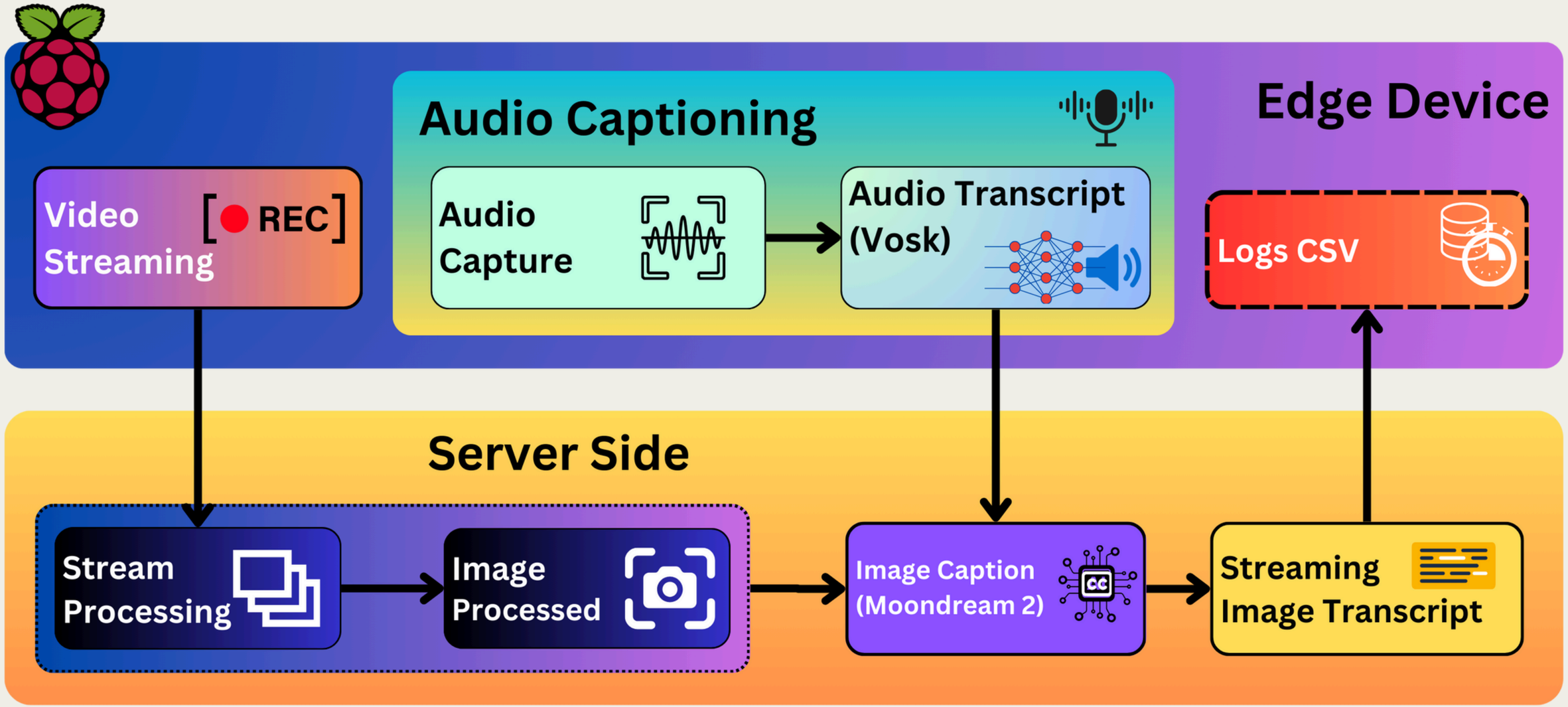


- The chart compares LLM models based on RAM requirements (GB) and model size (parameters in billions).
- TinyLLaMA (1.1B) and Mini LLaMA (1.1B) are resource-efficient, ideal for edge devices like Raspberry Pi.
- Larger models, such as Mistral (7B) and BTLM-3B-8K, have higher resource demands, making them less suitable for real-time, on-device applications.

Final Working DataFlow



Final Model Choice

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Chosen Stack:

- **Audio:** Vosk for offline transcription
- **Visual:** Moondream 2 for image-to-text captioning

Why This Combination?:

1. **Accuracy:** Vosk and Moondream 2 demonstrated reliable performance in capturing essential details without losing critical information.
2. **Efficiency:** Both models operated smoothly on low-power hardware, maintaining consistent performance without overheating or crashing.
3. **Privacy:** On-device processing meant no raw images, no audio files, and no personal data transmitted to external servers. This strictly preserved user confidentiality.
4. **Real-Time Response:** Low latency ensured immediate event logging and retrieval, supporting user queries like “What happened this afternoon?” promptly.

Bottom Line: This lean, integrated approach balanced quality insights, resource constraints, and privacy requirements, resulting in a practical, user-focused solution

Future Design

This is the design of a smartglasses created using an ESP32 which has a camera onto it and a processing unit with a battery to power it up for longer times.

Results & Insights

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Improved Recall Accuracy: Preliminary tests showed a significant boost in identifying and summarizing key events. For instance, conversational highlights were captured with greater than 90% transcription accuracy, while object recognition matched user experiences more closely than initial trials.

Real-Time Retrieval: User queries like “What happened at 3 PM?” returned concise summaries of the conversation topic, participants, and key actions within seconds.

Enhancing Cognitive Support: Users with memory challenges could rely on MEMLOG to quickly access a textual log of their day, reducing frustration and fostering independence.

Quantitative Highlights: Event detection accuracy improved by approximately 20% after refining the chosen models and removing resource-heavy, off-device processing.

Overall Insight: Achieved a stable system that balanced performance, privacy, and usability, reinforcing MEMLOG’s original mission.

Limitations & Considerations

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- **Hardware Constraints:** The Form Factor can be improved from a raspberry Pi to Esp32 based glasses or worked on a smartglasses
- **Accuracy Drift:** Models might lose accuracy over time if environmental conditions change or if new objects and contexts appear. Regular updates on objects or fine-tuning is necessary.
- **Ethical & Privacy Factors:** Although no raw images or audio are stored, users have to trust the device and the summaries.
- **User Control:** Providing mechanisms to delete, edit, or export summaries empowers users to maintain control over their data, mitigating privacy risks.
- **Future Room for Improvement:** Potential integration of more efficient models, better battery solutions, and incremental learning techniques to enhance system resilience and adapt to evolving user needs.

Conclusion

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Project Achievements:

- Developed and tested a IOT device algorithm, AI-driven memory aid that processes visual, audio, and motion data into concise, privacy-respecting text summaries.
- Identified optimal model combinations (Vosk + Moondream 2 + lightweight on-device LLM) that balance performance, privacy, and immediacy.

User Impact: The summaries could offer tangible support for individuals with memory challenges, professionals needing quick recall, and anyone wishing to better understand their daily experiences.

Learnings & Insights: Resource constraints and privacy concerns drove the project toward a lean, on-device strategy.

Next Steps:

- To explore more efficient local models, hardware accelerators, and user-centered trials to validate real-world effectiveness.
- Make the LLM work for efficient and better translations
- Improve adaptiveness, enabling the system to learn from evolving routines.
- Potential integration with wearable AR interfaces for more immersive feedback experiences.

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Discussion...

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Thank you!