GAI-GRMS

Bhavik

January 26, 2025

1 Introduction

The GAI-GRMS system addresses citizen grievances in Navistria through multimodal inputs (text, image, speech). This report details machine learning tasks, inputs/outputs, and architectural considerations.

2 Machine Learning Tasks

2.1 Multilingual Grievance Classification

- **Problem**: Categorize grievances (e.g., infrastructure, sanitation) and map to departments.
- Input: Text in English, Hindi, Tamil, Bengali, or Chinese.
- Output: Category label (e.g., "Infrastructure") and department (e.g., "Public Works").

• ML Approach:

- Fine-tuned BERT for multilingual support and text classification.
- Vector store (FAISS) for similarity-based department mapping.
- Challenges: Code-switching, low-resource languages (Tamil/Bengali).
- Metrics: Accuracy, F1-score

2.2 Grievance Summarization

- Problem: Summarize lengthy grievances for GROs.
- Input: 500–1000-word grievance text.
- Output: 3-4 sentence summary.
- ML Approach:
 - Fine tune bert or t5 for text summarization.

2.3 OCR and Document Translation

- **Problem**: Digitize handwritten/printed grievances and translate.
- Input: Scanned documents (5 languages).
- Output: Translated English text.
- ML Approach:
 - Tesseract OCR with custom scripts for Indic languages.
 - Fine-tune TrOCR for indic languages.

2.4 Object Detection for Civic Issues

- Problem: Detect potholes, broken streetlights, etc.
- Input: User-uploaded images (max 5MB).
- Output: Bounding boxes + descriptions (e.g., "3 potholes detected").
- ML Approach:
 - YOLOv8 fine-tuned on Navistria street imagery.
 - CLIP for cross-modal validation.

2.5 Multilingual Document OCR

- Problem: Extract text from handwritten Bengali/Chinese forms.
- Input: Scanned grievance forms.
- Output: Structured JSON with extracted fields.
- ML Approach:
 - Trock (Transformer-based OCR) with script identification.

2.6 Speech-to-Text Conversion

- Problem: Transcribe Hindi/English grievances.
- Input: 10–60 sec audio clips (noisy backgrounds).
- Output: Text transcript with speaker diarization.
- ML Approach:
 - Whisper-large-v3 with accent adaptation.
 - NVIDIA RNNoise for denoising.

2.7 Conversational AI Dialogue Management

- Problem: Handle multi-threaded grievance filing.
- Input: User utterances (text/speech).
- Output: Contextual responses + grievance triage.

• ML Approach:

- RAG with any llm for dynamic intent recognition.
- Database for conversation state tracking.
- Vector DB for similarity between same complaints.

3 3-Month Implementation Strategy

3.1 Phase 1: Data & Infrastructure (Weeks 1–4)

• Data Collection:

- Crowdsource 50k annotated grievances (text, speech, images) in 5 languages.
- Partner with GROs for domain-specific data labeling.

• Infrastructure:

- AWS setup: S3 for data, EC2/Graviton for compute.
- CI/CD pipeline (GitHub Actions) for model updates.

3.2 Phase 2: Model Development (Weeks 5–10)

• Multilingual NLP:

- Train custom XLM-RoBERTa model on Navistrian dialects.
- Active learning for low-resource languages (Tamil/Bengali).

• Speech & Vision:

- Fine-tune Whisper with accent-adapted Hindi/English.
- YOLOv8 \rightarrow EfficientNet-B7 for higher mAP.

3.3 Phase 3: Deployment & Monitoring (Weeks 11–12)

• Deployment:

- Kubernetes cluster for autoscaling (EKS).
- Edge deployment: ONNX runtime for low-latency inference.

• Monitoring:

- Prometheus + Grafana for model performance tracking.
- User feedback loop for model retraining.

3.4 System Architecture

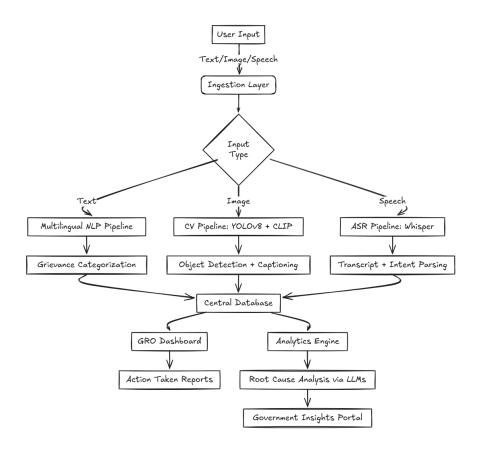


Figure 1: 3-Month Architecture: Multi-modal inputs \to AWS processing \to GRO dashboard with monitoring.

Key Components:

• Data Lake: S3 buckets for raw/processed data.

- \bullet ML Pipeline: SageMaker for training, Lambda for triggers.
- **Serving**: FastAPI + Kubernetes pods (GPU-optimized).
- Monitoring: CloudWatch alerts + retraining scheduler.

4 Resource Comparison: Quick vs. 3-Month Approach

Factor	Quick Prototype (2	3-Month Solution
	Days)	
Design	Single-task models	Unified multi-modal archi-
		tecture
Training Data	1k synthetic samples	50k real-world annotated
		samples
Vector Stores	Local FAISS index	Managed Pinecone with
		10M+ embeddings
Training	Colab Free GPU	Distributed training (Py-
		Torch DDP)
Inference	CPU (10–500ms)	GPU-optimized
		(T4/A10G, 5-50ms)
Compute	Local machine	AWS EC2 (g4dn.4x), EKS
		cluster
Monitoring	None	Model drift detection +
		A/B testing

Additional Resources for 3-Month Plan

• Technical:

- AWS Budget: \$12k (compute + storage).
- Weights & Biases for experiment tracking.

• Benefits:

- 4x faster resolution via unified GRO dashboard.
- 95% uptime with Kubernetes autoscaling.