Enhancing AI-assisted Stroke Emergency Triage with Adaptive Uncertainty Estimation

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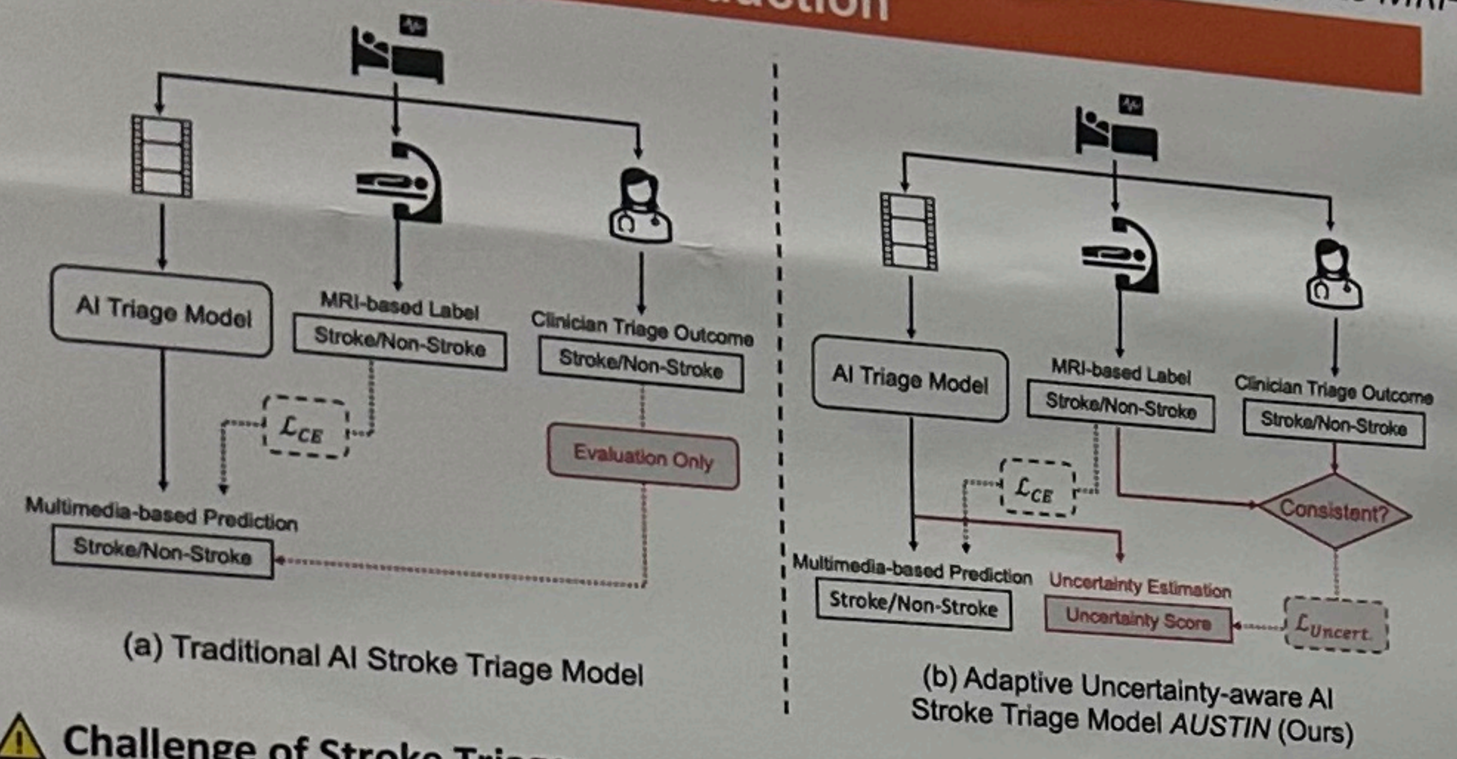
"AUSTIN: An adaptive, uncertainty-aware multimedia model that exploits MRI–triage disagreements to boost ER stroke triage accuracy and yield confidence scores."

Introduction



(a) Traditional AI Stroke Triage Model

(b) Adaptive Uncertainty-aware AI Stroke Triage Model *AUSTIN* (Ours)

Challenge of Stroke Triage:

- **High-stake, subtle signs:** Stroke patients risk disability/mortality; symptoms can be subtle.
- **Limited access to MRI in ER:** MRI is gold standard but often unavailable in ERs.
- **Capacity gap:** NIHSS needs expertise; neurologist shortage can lead to misdiagnoses.

Motivation for our new model AUSTIN:

- **Utilize triage labels:** Treat clinician triage as a complementary, informative signal.
- **Quantify uncertainty:** Calibrated uncertainty σ to flag ambiguous patient cases.
- **Learn from mismatches:** Use MRI–triage disagreements to boost robustness.

Method: AUSTIN

Data & Setting

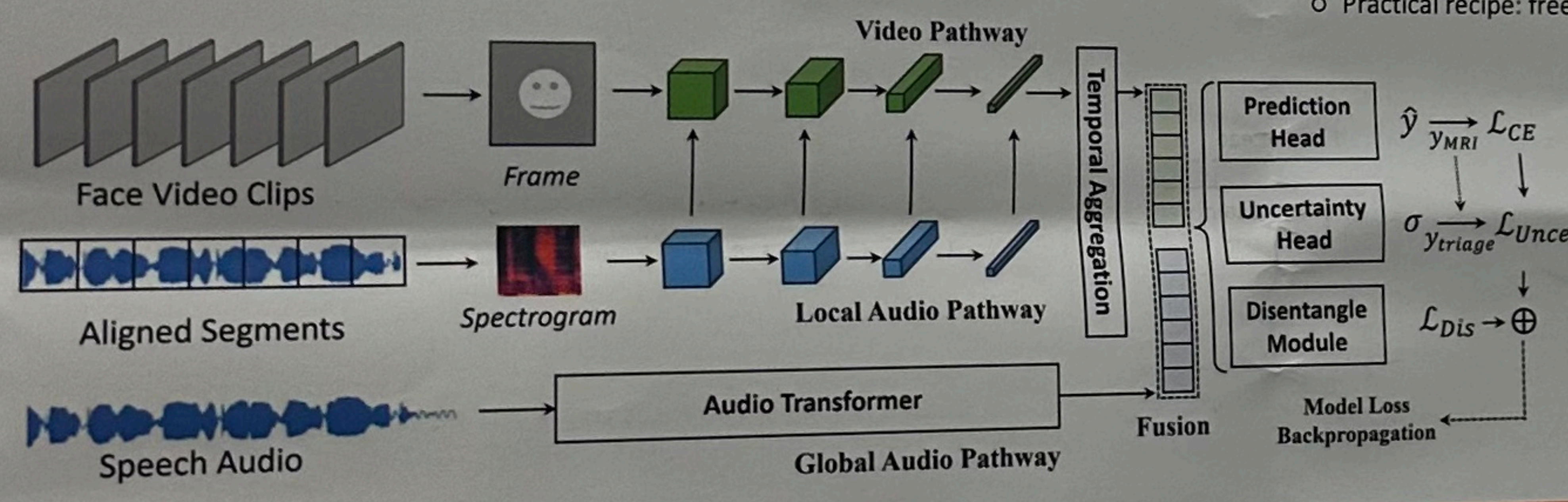
- **Cohort:** 249 ER patients (171+, 78-)
  - Diverse demographics
- **Temporal holdout:** 170/36/43 train/val/test.
- **Labels:**
  - MRI Label: binary groundtruth
  - Triage Label: ER clinician's impression label
- **Protocol:** "Cookie Theft" description video per NIHSS; paired audio recorded on mobile.

Model Framework

- **Multimedia encoder:**
  - Vido frame pathway: face frames → ResNet-50 (face-pretrained).
  - Local audio pathway: aligned spectrogram slices → ResNet-18, fused into frames.
  - Global audio pathway: full-utterance embedding → One-Peace transformer.
- **Temporal aggregation** with **S4** state-space layer; late fusion to final feature **h**.
- **Two heads:** *prediction* (stroke vs non-stroke) and *uncertainty* (σ).
- **Identity disentangling** via *adversarial discriminator* to reduce spurious cues.
- **Overall Training Objectives:**

$$\mathcal{L}_{\mathrm{Dis}} = \sum_{i,j} \|\delta_{ij} - \mathrm{D}(h_i, h_j)\|_2 , \qquad \mathcal{L}_{\mathrm{adv,E}} = -\sum_{i,j} \|0.5 - \mathrm{D}(h_i, h_j)\|_2 , \quad (2)$$

  - Penalize by learned uncertainty σ and MRI–triage agreement.
  - Practical recipe: freeze ResNet/One-Peace backbones; train S4, heads, and D.



Adaptive Uncertainty-Aware Loss

$$\mathcal{L}_{\mathrm{Uncert.}} = \frac{1}{2\sigma^2}\mathcal{L}_{\mathrm{CE}} + w \log(\sigma + \epsilon) , \quad w = \exp(-\alpha|y_{\mathrm{MRI}} - y_{\mathrm{triage}}|), \quad (1)$$

- **Labels Agree (w≈1):** Model is confident, σ is pushed lower.
- **Labels Disagree (w≈0): Model is uncertain, σ remains high.**
- The loss dynamically adapts to **clinician-MRI inconsistency.**
- Keep MRI as supervision but **learn to be uncertain** when MRI↔triage labels disagree.
  - σ both **regularizes training** (avoid overfitting to ambiguous cases) and **guides workflow** (route to imaging/expert).

Experiments & Results

Setup

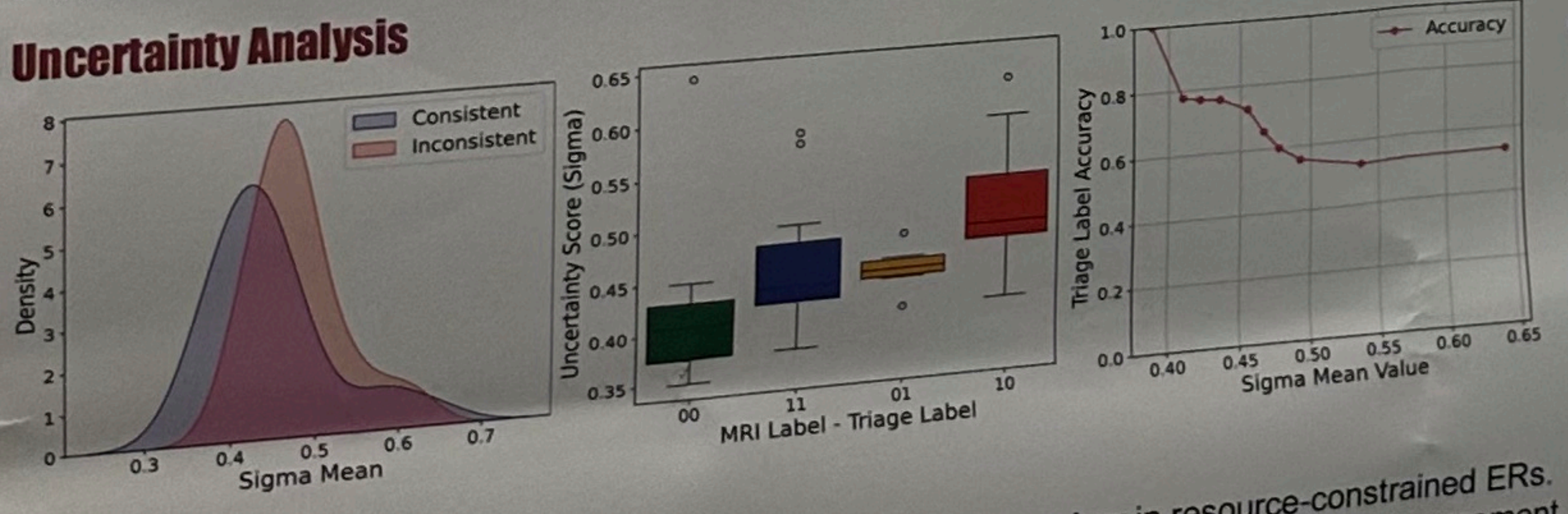
- **Preprocess:** PFLD face operations; N=7 clips, L=64 frames/clip; mel (M=128).
- **Backbones:** ResNet-50 (face video, FairFace-pretrained), ResNet-18 (local audio, ESC-50-pretrained), One-Peace (global audio).
- **Optimization:** batch size 32, lr 1e-4, dropout 0.2, 100 epochs on V100 (~6h).
- **Metrics:** Accuracy, Specificity, Sensitivity, **AUC**

Main Experiment

Model	Accuracy	Specificity	Sensitivity	AUC
Clinician Triage Performance	0.5349	0.5385	0.5333	-
DeepStroke	0.6977	0.6154	0.7333	0.6564
Proposed Encoder w/o $\mathcal{L}_{\mathrm{Uncert.}}$	0.6047	0.6923	0.7000	0.6658
+ $\mathcal{L}_{\mathrm{Uncert.}}$ w/ Fix $w=1$	0.6976	0.6154	0.7333	0.7128
+ Adaptive w (AUSTIN)	**0.7442**	**0.7692**	**0.7333**	**0.7897**

- Multimedia encoder and uncertainty formulation (fixed-weight) improves over DeepStroke;
- **Adaptive** weighting yields large AUC boost.

Uncertainty Analysis



- **Higher σ** on cases where MRI & triage **disagree** (distribution shift in KDE).
- Combination (MRI, triage)=(1,0) shows **highest median σ** → MRI-confirmed stroke with subtle/no outward signs.
- As σ-threshold increases, **triage-MRI consistency** drops → σ tracks case difficulty.
- Clinical use: σ can gate **further imaging or expert review.**

Ablations

Vision	Global Audio	Local Audio	Accuracy	Specificity	Sensitivity	AUC
ResNet50	One-Peace	ResNet18	0.6047	**0.6923**	0.7000	**0.6658**
ResNet50	AST	ResNet18	**0.6977**	0.6154	**0.7217**	0.6564
ResNet50	×	ResNet18	0.5584	0.4846	0.6333	0.5821
×	One-Peace	×	0.5814	0.4615	0.6333	0.5897
FaceXFormer	One-Peace	×	0.6279	0.6154	0.6333	0.6051
MARLIN	One-Peace	×	0.6279	0.5846	0.6667	0.6129

Clinical Implications

- **Triage safety:** High-σ cases are chosen for **MRI / expert review** in resource-constrained ERs.
- **Interpretability:** σ acts as an **intuitive confidence signal**, aligned to clinician–MRI agreement.
- **Generalization:** The adaptive uncertainty paradigm can extend to other tasks where multimodal inputs and diagnostic labels disagree.

Conclusion

- AUSTIN integrates **adaptive uncertainty** with multimedia encoders for ER stroke triage.
- It delivers **SoTA** performance and **actionable σ** for workflow decisions.
- Its added interpretability improves reliability in resource-constrained ERs.

Future Work

- **Prospective, multi-site validation** and larger cohorts; fairness & subgroup analyses.
- **Calibrated uncertainty** (temperature scaling, conformal) and per-segment σ.
- **Active/triage routing:** learn policies for MRI image vs. observe vs. discharge.

References

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