FAST.AI: A Novel Approach for Rapid Stroke Detection Using Edge AI

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Introduction

Stroke is a leading cause of death and long-term disability, with over 12 million cases each year. Globally, 101+ million people are currently living with the long-term aftermath effects of stroke. FAST.AI addresses this urgent need by empowering individuals to screen for stroke symptoms at home or on the go, using the clinically validated, 87.5% accurate FAST protocol: **Face** drooping, **Arm** weakness, **Speech** difficulty/slurring, and **Time** to call emergency services.

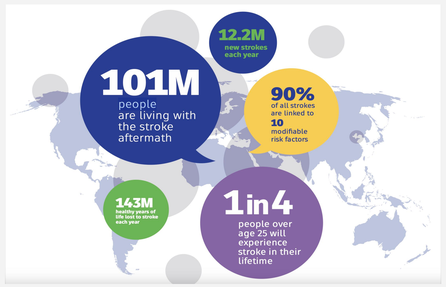


Fig. 1: Stroke Facts (2021)

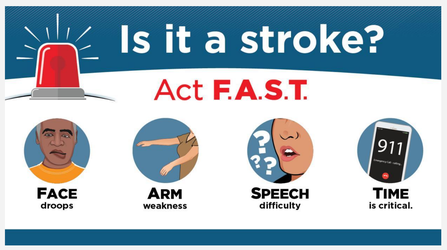


Fig. 2: The F.A.S.T. Acronym

By integrating this protocol into a mobile app powered by AI, FAST.AI delivers accessible, real-time stroke screening without the need for specialized hardware.

Research Question

Can we use multimodal AI tools to reliably detect real-time asymmetries associated with stroke through mobile devices?

Technology and Methedology

Facemesh algorithms

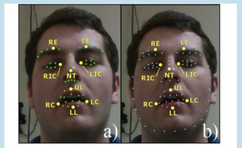


Figure 1: *Facial landmarks obtained with SDM (a) and IntelFT (b). The points of interest for feature extraction are highlighted in yellow.*

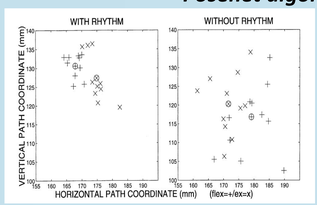
Points Around The Mouth Used in FaceMesh Algorithm (8)

Table 4: *Statistical significant differences during the BBP, BLOW, and SPREAD tasks (*p<.05, **p<.001)*

Task	Feature	HC subjects	Patients PS
BBP	$A_{diff}(mm^2)$	16.56±9.60	35.20±20.95*
	$d_{LLdiff}(mm)$	1.12±0.65	2.28±1.27*
BLOW	$W_{MAX}(\%)$	2.14±8.36	-6.34±7.82*
	$A_{diff}(mm^2)$	17.74±10.33	42.62±28.12*
SPREAD	$A_{diff}(mm^2)$	8.08±4.23	23.78±24.67**
	r_{LCRC}	0.76±0.22	0.40±0.47*
	$d_{LCdiff}(mm)$	1.25±0.98	2.70±1.76*

FaceMesh Area Difference Algorithm (8)

Posenet algorithms/data



Stroke vs. Regular Arm Data Points (2)

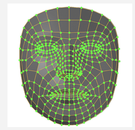
Table 1: *Mean value and standard deviation of ROM and asymmetry scores across the participant groups considered in the study*

	HC subjects	Patients PS	% Agreement	κ
ROM	1.06±0.13	1.80±0.45	68.9%	0.50
Asymm	1.31±0.22	2.33±0.70	58.7%	0.55

Posenet Algorithm Score Deviation (8)

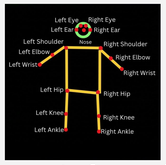
FaceMesh - *Face*

FaceMesh is an AI tool from Google MediaPipe that uses deep neural networks and takes 486 landmark points on a person's face for precise facial feature analysis. Our method identifies facial asymmetries critical for stroke detection by comparing specific facial landmarks. Using the metrics provided by Bandini et al., we calculated and compared the area differences on 4 points on the mouth during actions like "Buy Bobby a puppy" (**BBP**), "blow a candle" (**BLOW**), and "pretending to smile with closed lips" (**SPREAD**).



PoseNet - *Arms*

PoseNet enables real-time skeletal tracking of the body using a complex neural network architecture that uses heatmaps and offset vectors to determine the exact positions of these points. Users raise both arms in front of them, and the app measures deviations from a horizontal baseline. We developed custom algorithms that calculate the angles and distances between joints to flag asymmetric arm positions or drifts, which are common in acute stroke cases.



Speech to Text - *Speech*

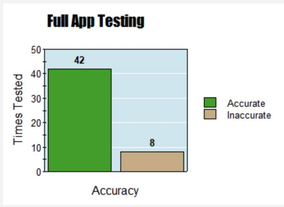
We integrated Google's Speech to Text model to accurately detect slurred speech using our own algorithm. Users are instructed to say a short sentence, which is compared to a sample sentence from a healthy patient, and is given a sub-result based on clarity.

Conclusion & Application

Accurate
The FAST proven diagnostic points directly at clinically validated stroke signs. Facial asymmetry, arm drift, and slurred speech are assessed using real-time computer vision and speech AI backed by peer-reviewed research.

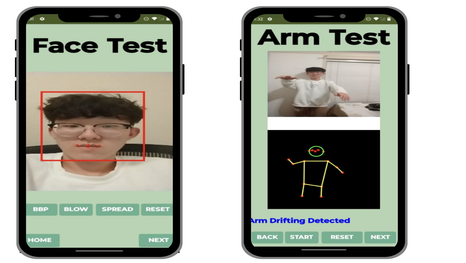
Interpretable
The results are translated into easy-to-read visuals and actionable prompts. A built-in AI assistant can answer concerns in plain language, offering guidance as needed.

Accessible
FAST.AI runs on standard mobile device hardware, allowing for widely accessible stroke screening. The simple user interface is designed with large buttons to support elderly or impaired users.



App Testing

Mobile App Demo



Discussion

At the time, we did not have confirmed stroke patient data at our disposal, so we tested the accuracy of the app by mirroring stroke symptoms ourselves. We recorded results on a Google Sheet, achieving an 84% accuracy, closely reflecting the performance of clinical professionals (87.5%). To further improve these numbers in the future, we plan to conduct clinical trials and patient surveys to collect real-world data.

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References/Sources

1. *https://www.generationshcm.com/blog/2019/06/how-to-spot-the-warning-signs-of-a-stroke*
2. *M. H. Thaut, G. P. Kenyon, C. P. Hurt, G. C. McIntosh, V. Hoemberg, Kinematic optimization of spatiotemporal patterns in paretic arm training with stroke patients. Neuropsychologia 40, 1073-1081 (2002).*
3. *A. M. Nor et al., Agreement between ambulance paramedic- and physician-recorded neurological signs with Face Arm Speech Test (FAST) in acute stroke patients. Stroke35, 1355-1359 (2004).*
4. *J. Kennedy et al., Fast assessment of stroke and transient ischaemic attack to prevent early recurrence (FASTER): a randomised controlled pilot trial. The Lancet Neurology 6, 961-969 (2007).*
5. *D. O. Kleindorfer et al., Designing a message for public education regarding stroke: does FAST capture enough stroke? Stroke 38, 2864-2868 (2007).*
6. *Awareness of stroke warning symptoms--13 States and the District of Columbia, 2005. MMWR. Morbidity and mortality weekly report 57, 481-485 (2008).*
7. *T. D. Musuka, S. B. Wilton, M. Traboulsi, M. D. Hill, Diagnosis and management of acute ischemic stroke: speed is critical. CMAJ : Canadian Medical Association journal = journal de l'Association medicale canadienne 187, 887-893 (2015).*
8. *A. Bandini, J. Green, B. Richburg, Y. Yunusova, Automatic Detection of Orofacial Impairment in Stroke. (2018), pp. 1711-1715.*
9. *G. Jackson, K. Chari, National Hospital Care Survey Demonstration Projects: Stroke Inpatient Hospitalizations. National health statistics reports, 1-11 (2019).*
10. *K. Lai, M. Almekhlafi, S. Yanushkevich, in 2023 IEEE Symposium Series on Computational Intelligence (SSCI). (2023), pp. 1032-1037.*
11. *A. M. Pecunda, P. A. Abu, R. Alampay, Amyotrophic Lateral Sclerosis and Post-Stroke Orofacial Impairment Video-based Multi-class Classification. (2023), pp. 150-157.*
12. *C. W. Tsao et al., Heart Disease and Stroke Statistics-2023 Update: A Report From the American Heart Association. Circulation 147, e93-e621 (2023).*
13. *CDC. (CDC WONDER Database, 2024).*
14. *S. S. Martin et al., 2024 Heart Disease and Stroke Statistics: A Report of US and Global Data From the American Heart Association. Circulation 149, e347-e913 (2024).*
15. *B. Mirheidari, S. M. Bell, K. Harkness, D. Blackburn, H. Christensen, Spoken language-based automatic cognitive assessment of stroke survivors. Language and Health 2, 32-38 (2024).*
16. *Z. Ou et al., Early identification of stroke through deep learning with multi-modal human speech and movement data. Neural regeneration research 20, 234-241 (2025).*
17. *M. Uppal et al., Enhancing accuracy in brain stroke detection: Multi-layer perceptron with Adadelta, RMSProp and AdaMax optimizers. Frontiers in Bioengineering and Biotechnology 11, (2023).*
18. *G. C. Oliveira et al., Facial expressions to identify post-stroke: A pilot study. Computer Methods and Programs in Biomedicine 250, 108195 (2024).*
19. *A. Elhanashi, P. Dini, S. Saponara, Q. Zheng, TeleStroke: real-time stroke detection with federated learning and YOLOv8 on edge devices. Journal of Real-Time Image Processing 21, 121 (2024).*
20. *I. Grishchenko, A. Ablavatski, Y. Kartynnik, K. Raveendran, M. Grundmann, Attention Mesh: High-fidelity Face Mesh Prediction in Real-time. ArXiv abs/2006.10962, (2020).*
21. *A. R. Priyadharshini, R. Annamalai, Identification and Reconstruction of Human Faces into 3D Models Using SSD-Based and Attention Mesh Models in Real-Time. SN Computer Science 5, 1092 (2024).*
22. *Y. Kartynnik, A. Ablavatski, I. Grishchenko, M. Grundmann, Real-time Facial Surface Geometry from Monocular Video on Mobile GPUs. (2019).*
23. *E. Park, H.-J. Chang, H. S. Nam, Use of Machine Leaning Classifiers and Sensor Data to Detect Neurological Deficit in Stroke Patients. Journal of Medical Internet Research 19, e120 (2017).*
24. *https://livinghealthy.hawaii.gov/stroke/stroke-risk-factor/*
25. Crause K, Stassen W. The accuracy of the FAST stroke assessment in identifying stroke at initial ambulance call into a South African private emergency call centre. South Afr J Crit Care. 2020 Jul 30;36(1):10.7196/SAJCC.2020.v36i1.399. doi: 10.7196/SAJCC.2020.v36i1.399. PMID: 37287991; PMCID: PMC10243601.

Acknowledgements

- Ms. Holly Liao, Coach: helped us overview the entire project.
- Our Parents: gave us helpful insight based on their medical backgrounds and went out of their way to support us in our endeavors.
- Dr. Yu Meng, Mentor: provided great insight and feedback on our app.