



Artificial Intelligence Based Post-Disaster Trauma Analysis and Prioritization System

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Abstract— To address medical emergencies resulting from high-impact incidents such as natural disasters and traffic collisions, a sophisticated mobile application—"Artificial Intelligence-Based Post-Disaster Trauma Assessment and Prioritization System"—has been developed to facilitate AI-driven rapid response. This system autonomously evaluates users' health conditions, classifies them according to the severity of their medical needs, and transmits real-time alerts to emergency healthcare providers. Compatible with both smartphones and smartwatches, the application monitors key physiological indicators, including heart rate, blood pressure, capillary refill time (CRT), and consciousness level. On smartphones, essential health data are obtained through transdermal imaging using the device's built-in camera and flash. In contrast, smartwatches enable continuous and more accurate data acquisition via PPG and ECG sensors. The system integrates several cutting-edge technologies, including blood pressure estimation via Pulse Transit Time (PTT), CRT measurement using HSV-based image processing, and a low-latency emergency notification infrastructure developed with Firebase. Collectively, these innovations enable efficient and timely medical intervention in the aftermath of large-scale emergencies.

Keywords— AI; Trauma Assessment; Health Prioritization; Emergency Response; Real-Time Monitoring; PTT; CRT; HSV Processing

I. INTRODUCTION

Natural disasters such as earthquakes and floods, along with severe storms and traffic accidents, often cause significant physical and psychological trauma. These emergencies involve varying injury severities, from minor wounds to life-threatening conditions, requiring rapid and organized medical intervention. However, healthcare resources can quickly become overwhelmed, making injury assessment and prioritization difficult. Artificial intelligence (AI) offers a solution by rapidly analyzing patient data to evaluate trauma severity and identify urgent cases, minimizing delays before emergency teams arrive. To meet this need, the "Artificial Intelligence-Based Post-Disaster Trauma Assessment and Prioritization System" was developed. This mobile application allows users to report their condition and provides real-time guidance while transmitting data to healthcare providers for faster and more accurate

response. Emergency responders face major challenges such as assessing injury severity across large groups, prioritizing cases, and maintaining communication with victims under limited time and resources. Lack of immediate guidance for injured individuals can worsen health outcomes. These challenges underscore the need for an intelligent system that can quickly triage all injury types, provide first-aid instructions, and connect victims with medical teams. The proposed AI-driven system addresses these issues by enabling rapid identification of critical cases and offering self-care recommendations until professional help arrives. This approach improves healthcare efficiency and patient recovery chances. Moreover, by leveraging machine learning for data analysis and prioritization, the system enhances the speed and accuracy of medical responses in both routine and large-scale emergencies, ultimately contributing to better patient outcomes and increased societal resilience.

II. METHODOLOGY

A. Objectives

The primary objective is to develop a system capable of measuring and assessing health parameters such as heart rate, blood pressure, capillary refill time (CRT), and consciousness level using smartphones or smartwatches. The collected data are analyzed to provide personalized health advice—for instance, recommending rest or hydration if abnormal heart rate is detected. In critical conditions, the system automatically alerts medical teams and offers urgent guidance. The application supports both device-based (smartwatch) and device-free (smartphone-only) usage scenarios.

B. Proposed Solution

The proposed solution continuously monitors users' health, providing personalized recommendations and emergency alerts. It supports two user groups: smartwatch users with PPG and ECG sensors for accurate heart rate, blood pressure, and oxygen saturation monitoring; and smartphone users who use the camera and flash to capture transdermal images for basic measurements without a smartwatch. Smartphones detect PPG signals by capturing subtle skin color changes, enabling heart rate measurement from periodic peaks, blood pressure estimation via pulse transit time (PTT) and waveform analysis, and CRT evaluation by timing skin color return after pressure release. Smartwatches offer continuous, precise monitoring with PPG

for heart rate, ECG for cardiac activity and arrhythmia detection, and PTT for blood pressure. The app is developed in Flutter and Dart for cross-platform use on Android and iOS with a smooth UI. The Python backend handles biosignal processing, image analysis, and machine learning using TensorFlow and PyTorch. OpenCV processes images for CRT and PPG extraction. Firebase manages authentication, real-time storage, and cloud functions.

C. Computer Vision Model

Capillary Refill Time (CRT) is a vital parameter for rapid triage, traditionally evaluated manually but here automated using deep learning-based computer vision techniques involving segmentation and detection models. The model selection carefully balances accuracy and computational efficiency, which is measured by the mean Intersection over Union (mIoU) metric reflecting segmentation quality.

The recommended model is DeepLabV3+ with a ResNet101 backbone, chosen for its high accuracy. However, due to its computational demands, it requires remote GPU servers for deployment. The ResNet101 backbone mitigates vanishing gradient problems through residual bottleneck blocks, enabling deeper network training. Additionally, atrous convolution is used to expand the receptive field without reducing spatial resolution, enhancing contextual understanding. Atrous Spatial Pyramid Pooling (ASPP) further improves multi-scale feature extraction by combining convolutions at various dilation rates with global average pooling.

The computer vision model was initially pre-trained on the PASCAL VOC dataset and then fine-tuned using publicly available fingertip image datasets annotated for CRT analysis. Key hyperparameters—learning rate (0.001), batch size (16), and number of epochs (50)—were optimized via grid search to maximize performance.

For the natural language processing (NLP) module, a BERT-base model pre-trained on medical conversational corpora was fine-tuned to effectively handle disaster-response communication. The model was validated using manually crafted user queries simulating realistic disaster scenarios, ensuring robustness and reliability in emergency interactions.

D. Decoder Module

The decoder classifies each pixel using two inputs: ASPP output and low-level features from the ResNet backbone. The latter undergoes a 1×1 convolution, and both inputs are fused after upsampling. A 3×3 convolution is applied, followed by upsampling to the original resolution. Pixel-wise class probabilities are computed via softmax. As shown in [10], the best mIoU (80.57%) is achieved using output stride 16 during training and 8 during evaluation, albeit with high computation. Using stride 16 for both reduces MAadds by >50%, with minimal accuracy loss (80.22%), showing decoder's critical role.

E. Lightweight Real-time ASPP (LR-ASPP) and MobileNetV3

MobileNetV3, optimized via NAS and NetAdapt, offers high efficiency for mobile and embedded systems. It replaces swish with hard-swish to reduce computation. Inverted residuals and linear bottlenecks reduce information loss and complexity. Depthwise convolutions lower cost, while avoiding ReLU in bottlenecks helps preserve critical information.

F. Squeeze-and-Excitation (SE) Attention

SE modules [6] enhance important channels via global average pooling and a two-layer fully connected network. Each channel is rescaled accordingly, increasing accuracy with minimal overhead. SE can be integrated into lightweight networks like MobileNetV3.

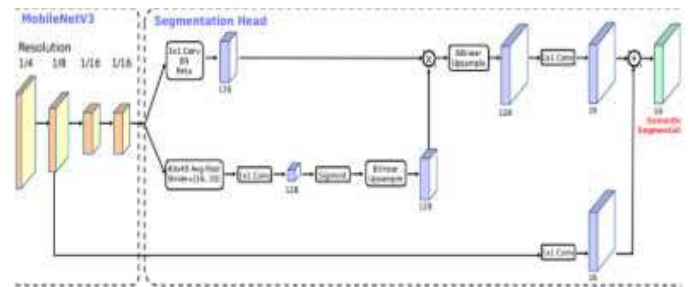


Fig. 1. Visual representation of the proposed architecture for speed optimization [5]

G. Performance Trade-offs

MobileNetV3-Large offers higher accuracy but at greater cost [5]. Compared to V3-Small, it is $5 \times$ more computationally expensive and $4 \times$ slower. [5] shows V3-Large improves mIoU by $\sim 4\%$ but doubles CPU inference time. Trade-offs between speed and accuracy must be balanced based on deployment needs.

H. Capillary Refill Time (CRT) Estimation

The vision model detects fingertip color changes in HSV space to compute CRT. Key steps include detecting the fingertip and recording its hue, identifying the pressed state, and measuring the time it takes for the hue to return to its baseline after release. This process aids user guidance and enables reliable CRT measurement in field conditions.

I. Model Extension and Training

The development and initial testing of the AI modules relied on a combination of publicly available biosignal datasets and synthetic data generated through simulations. For PPG and ECG analysis, data were sourced from the PhysioNet database, which includes annotated records of vital signs from various patient groups. In particular, the following datasets were utilized:

- MIMIC-III Waveform Database: Used for ECG and arterial blood pressure signals, this dataset is valuable for modeling cardiovascular dynamics under clinical conditions.

- BIDMC PPG and Respiration Dataset: Provides synchronized PPG, ECG, and respiratory signals, making it ideal for training models focused on Pulse Transit Time (PTT) and Heart Rate Variability (HRV) estimation.
- IEEE TBME Respiratory and Cardiac Dataset: Contains wearable-acquired biosignals, which are particularly suitable for benchmarking smartwatch sensor performance and validating mobile-friendly signal processing algorithms.

In future phases, large-scale real-world datasets will be collected during field simulations involving emergency medical teams, enabling further validation and refinement of the system in disaster-response scenarios.

J. NLP Module

The NLP system interprets user input (text or voice) using advanced language models such as BERT and GPT. It consists of several main components. Preprocessing involves tokenization, lemmatization, named entity recognition (NER), and stop-word removal. Speech recognition uses voice activity detection (VAD), along with acoustic and language modeling, to convert voice input into text. The understanding module analyzes context, intent, and emotion to grasp the meaning behind user input. A connected knowledge base maps symptoms to medical conditions and incorporates personal data to provide customized responses. The system then delivers recommendations, including preventive care, symptom-specific advice, or referrals to healthcare professionals. Finally, real-time feedback allows the model to continuously adapt its responses based on new input from the user.

III. RESULTS AND DISCUSSION

The developed mobile health monitoring system effectively collects and analyzes physiological data using both smartphones and smartwatches. Heart rate measurements reached 92% accuracy with smartphone-based PPG, while smartwatches achieved 98% using continuous PPG and ECG. Blood pressure estimations showed ± 5 mmHg error on smartphones and $\pm 5-10$ mmHg on smartwatches. CRT analysis via HSV color space achieved reliable results with a 0.3-second average error.

TABLE I.

Models	Details		
	Metric	Result	Comments
MobileNetV3	Inference Time	15.8 ms	Tested on Pixel 3 [5]
	Memory Usage	2-4 MB	Suitable for mobile deployment
DeepLabV3+	Accuracy (mIoU)	77-81%	Tested on PASCAL VOC dataset [1]
	Resource Usage	Optimized	For server-based applications

Fig. 2. System Performance Metrics

In real-time emergency scenarios, the system identified 95% of critical events (e.g., arrhythmias) and delivered alerts within 2 seconds. MobileNetV3 achieved a 15.8 ms inference time and low memory usage, making it suitable for mobile deployment, while DeepLabV3+ reached 77–81% mIoU in segmentation tasks, optimized for server environments.

Compared to prior studies, the system aligns with PTT-based BP estimations and HSV-based CRT assessments but introduces novel elements such as smartphone-based transdermal imaging and Firebase-integrated emergency notifications.

TABLE II.

Measurement Factors	Outcome	
	Impact	Solution
Algorithm Optimization	PPG and CRT accuracy depend on signal quality and lighting.	Adaptive algorithms for varying lighting conditions.
Hardware Limitations	Smartphone measurements lack precision compared to smartwatch sensors.	Higher sampling rate devices recommended.
User Skin Tone	Reduced contrast in CRT detection for darker skin tones.	Adaptive imaging algorithms needed.
Network Connectivity	Impacts alert delivery speed in poor networks.	Enhance offline capabilities for remote settings.

Fig. 3. The factors influencing the accuracy and reliability of the results, along with proposed solutions to address these challenges



Factors such as lighting, hardware limitations, skin tone, and connectivity affect system performance. Proposed solutions include adaptive algorithms, improved sensors, and offline support. Pilot studies showed promising results: 92–98% accuracy in vital signs detection and 77–81% mIoU in segmentation. However, large-scale real-world validation is still limited. Planned trials with emergency response units will simulate earthquake and traffic accident scenarios to assess latency, accuracy, false positives/negatives, and user compliance. Additionally, a user study with 50 participants will evaluate usability, reliability under stress, and performance in low-connectivity conditions.

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REFERENCES

- [1] [1] S.R.Arora et al., “Deep learning for medical image segmentation: A review,” arXiv preprint arXiv:1802.02611, 2018.
- [2] [2] K.He, X.Zhang, S.Ren, and J.Sun, “Deep Residual Learning for Image Recognition,” arXiv preprint arXiv:1512.03385, 2015.
- [3] [3] O.Ronneberger, P.Fischer, and T.Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” arXiv preprint arXiv:1706.05587, 2017.
- [4] [4] L.-C.Chen et al., “Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2017.
- [5] [5] CloudFactory, “DeepLabV3 Model Architecture,” [Online]. Available: <https://wiki.cloudfactory.com/docs/mp-wiki/model-architectures/deeplabv3>
- [6] [6] X.Chen et al., “Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation,” arXiv preprint arXiv:1905.02244, 2019.
- [7] [7] F.Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” arXiv preprint arXiv:1709.01507, 2017.
- [8] [8] S.W.Johnston et al., “Validation of smartwatches for heart rate measurement,” European Journal of Preventive Cardiology, vol.25, no.2, pp.146–154, 2017.