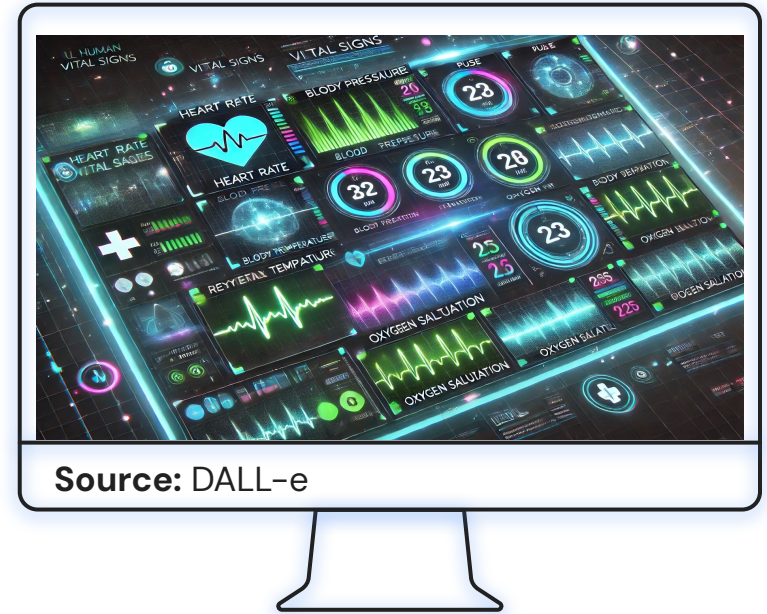


Capturing Biometric Signs Through Camera

Final Presentation

MARCH 13, 2025



Presentation Outline

- Objective
- Problem Statement & Use Cases
- Vital Signs approaches and Models
- User Interface Demo
- Project Challenges and Mitigation Strategy
- Recommendation for Future Steps

Objective

Develop an AI-powered solution that captures and assesses vital biometric signs using standard camera devices and open-source datasets.

- Body temperature,
- Blood pressure,
- Oxygen saturation,
- Heart rate

This innovation aims to deliver healthcare diagnostics to underserved communities, especially in semi-urban and rural areas.

Problem Statement & Use Cases

Problem Statement:

Barriers to essential healthcare diagnostics rural and semi-urban areas due to high costs, reliance on specialized technology, and poorly resourced facilities, underscoring the need for affordable, accessible solutions.

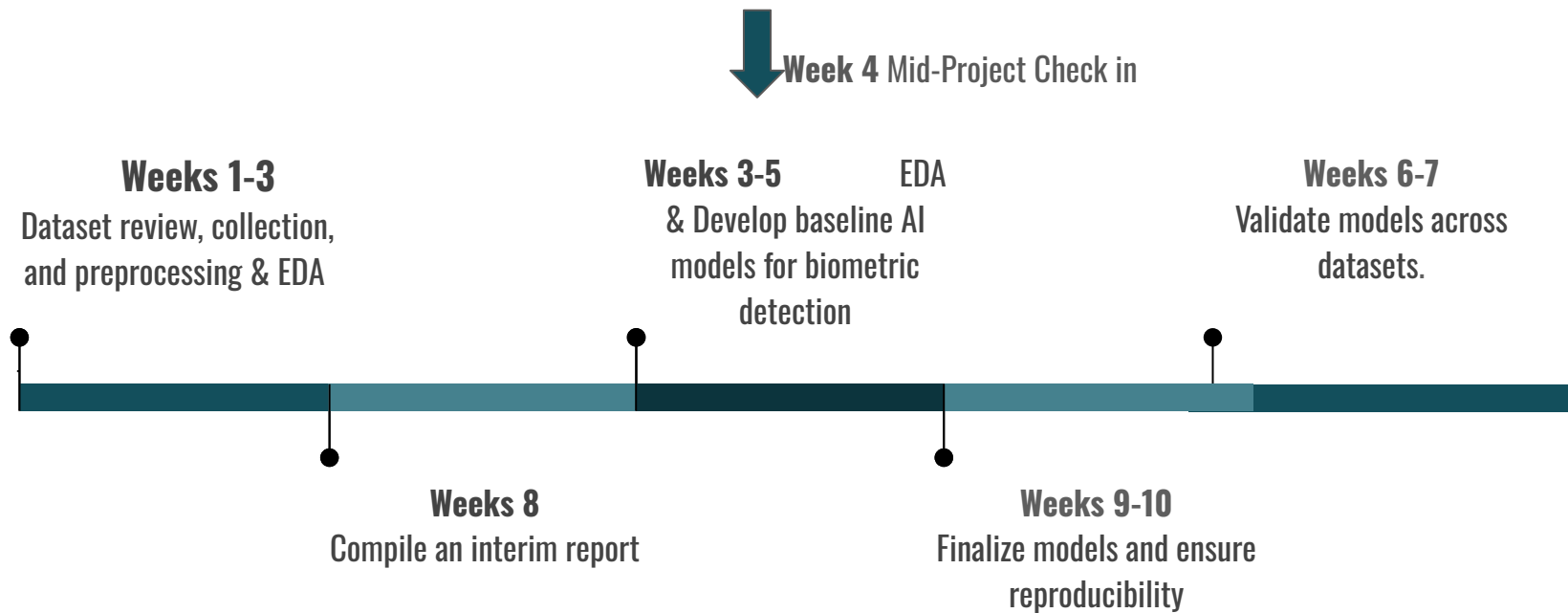
Purpose:

Project aims to leverage AI-powered, camera-based biometric monitoring to bridge healthcare accessibility gaps, providing underserved communities with timely and affordable diagnostics.

Use Cases:

- **Vital Sign Monitoring-** Enable camera-based monitoring of health metrics.
- **Telehealth Integration-** Enable telehealth platforms to remotely assess patient vitals.
- **Population Health Analytics-** anonymized data to advance public health research and interventions.

Project Roadmap



Datasets for Vital Signs

- **Data Sources:** Open source - V-BPE, PPG, UBFC
- **Type of Data Collected:**
 - **Image/Video Data** - Video, Image and PPG signals
 - **Physiological Data** - Pulse, BP (Systolic & Diastolic BP)
 - **Metadata** - Age, Height, Weight, Gender, BMI
- **Challenges in Data Collection:** Less number of open source dataset and dataset is limited to research purpose and not for commercial usage

Dataset Details

- V-BPE dataset - Dataset has vitals such as Heart Rate and BP (Systolic & Diastolic). Preprocessed videos and metadata information and filtered videos on dark skin tone. Dataset size reduced from 81 GB to 35.13 GB.
- PPG dataset - Dataset has vitals such as Heart Rate and BP (Systolic & Diastolic). Instead of patient videos the dataset has Photoplethysmogram signal.

Vital Sign Model Development

Task Lead Nishrin Kachwala

Vital Signs Model Development

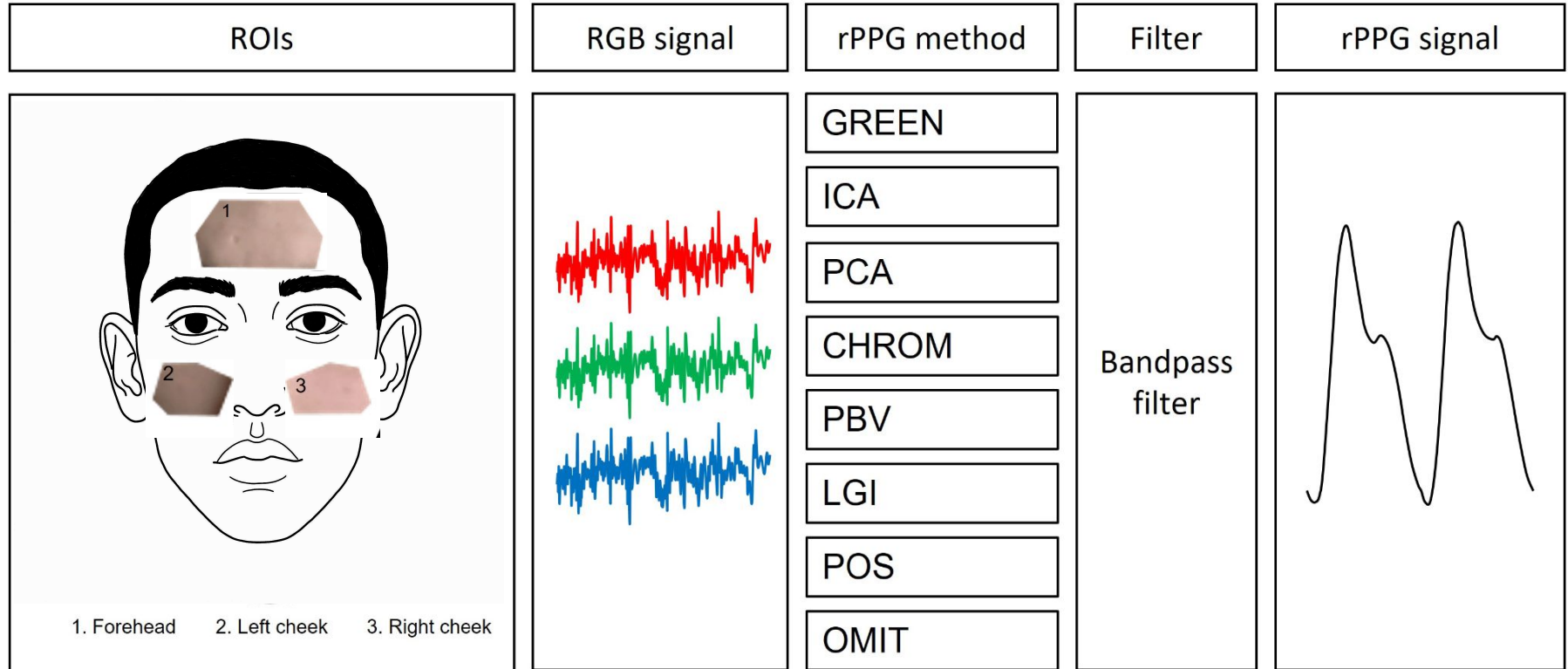
Heart Rate (HR) Estimation

Blood Oxygen Saturation (SpO₂) Estimation - Approximate

Blood Pressure (BP) Estimation

Body Temperature (out of scope using video input)

rPPG for Vitals Signs



Physiological Measurement Techniques

1. Heart Rate (HR):

- Detect peaks in the rPPG signal.
- Calculate heart rate using the peak intervals.

2. Blood Pressure (BP):

- **Signal Morphology Analysis:**

- Analyze rPPG signal features (e.g., systolic and diastolic peaks).

- **Pulse Transit Time (PTT):**

- Calculate PTT by measuring the delay between rPPG and other signals (e.g., foot of the pulse wave).

- Use machine learning models trained on labeled data to predict BP values.

3. Blood Oxygen Saturation (SpO₂):

- Extract red and blue channel intensities.
- Compute the absorption ratio to estimate SpO₂ values.

Temperature - Physiological Measurements

Temperature measurement Challenges:

- Variability in Video Quality, Facial Detection and Tracking, Physiological Variability
- Thermal Imaging vs. RGB: Most videos are captured using RGB cameras, which don't provide direct thermal information. This requires indirect estimation methods, can be less accurate.

We are not pursuing model development for temperature measurements due to lack of thermal imaging data

Preprocessing Techniques for Camera Data

- **Image Enhancement:**

- Denoising algorithms (e.g., Butterworth filter or wavelet transforms) to handle to handle noisy data.

- **Region-of-Interest (ROI) Extraction:**

- Focus on areas like skin (for SpO_2 , heart rate) to reduce computational complexity. We talked about using 30 fps Sampling Rate and Resolution of 640×480 pixels per frame

Heart Rate (HR) and Respiratory Rate (RR):

Remote Photoplethysmography Imaging (rPPG):

- Detect subtle color changes in the skin caused by blood flow using RGB data.
- Algorithms:
 - CHROM algorithm: Separates chromatic components to enhance blood flow detection.
 - POS algorithm: Uses the plane-orthogonal-to-skin method for better signal extraction.
- Use frequency analysis (e.g., FFT or wavelet transforms) to estimate heart and respiratory rates.

Heart Rate Estimation

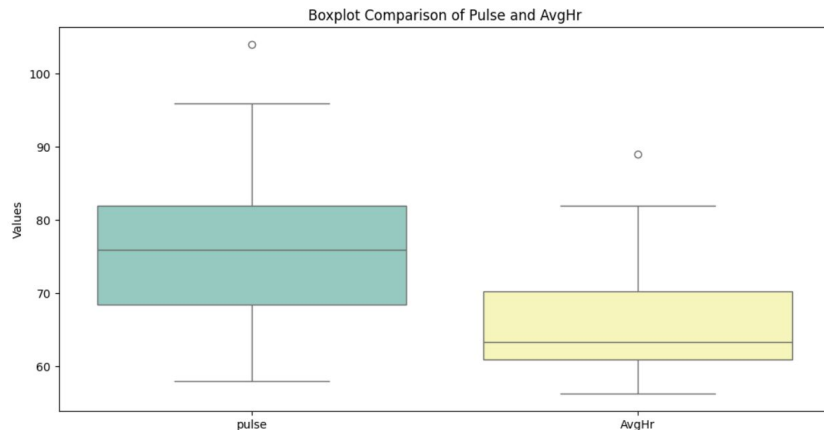
- **Region of Interest (ROI) Selection:** Used MediaPipe for face detection and extraction. Select the region of the video frame that contains the relevant physiological information (e.g., the face or a specific blood vessel). Cheeks and Forehead.
- **Filters applied then Color Channel Extraction:** The color channels (e.g., red, green, and blue) are extracted from the ROI.
- **HR - Green Channel Analysis:** Extract the green channel intensity over time. Use the pixel values to track subtle skin color changes caused by blood volume variations.

Heart Rate Estimation

- **Signal Post-Processing:**

- Apply bandpass filters to isolate the physiological frequency band (e.g., 0.7–4 Hz for HR).
- Estimate Heart Rate using FFT.

Boxplots illustrate the comparison between real heart rate (pulse) and predicted heart rate (AvgHR), using averages calculated from the forehead and both cheeks.



Metrics

Mean Squared Error (MSE): 282.4468
Root Mean Squared Error (RMSE): 16.8062
Mean Absolute Error (MAE): 13.6217

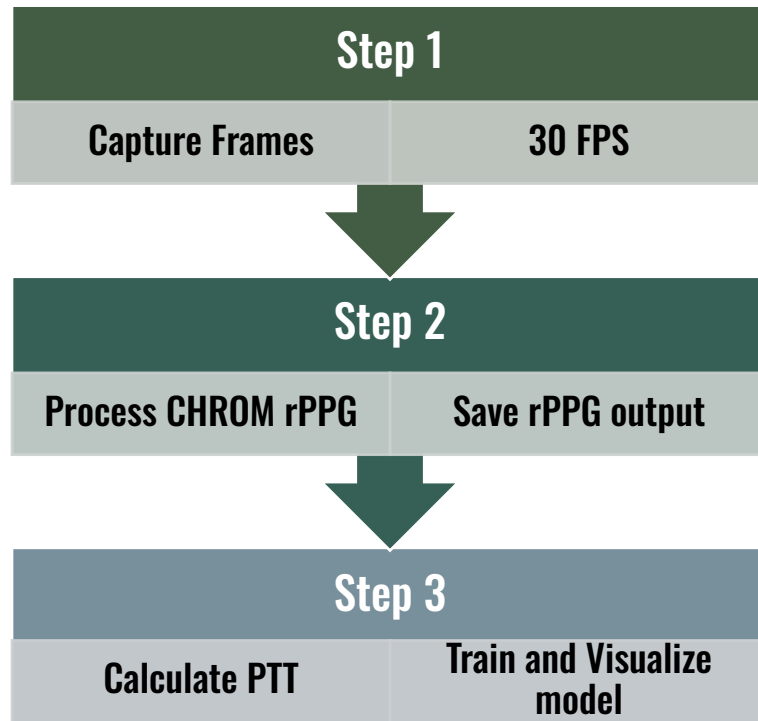
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Blood Pressure

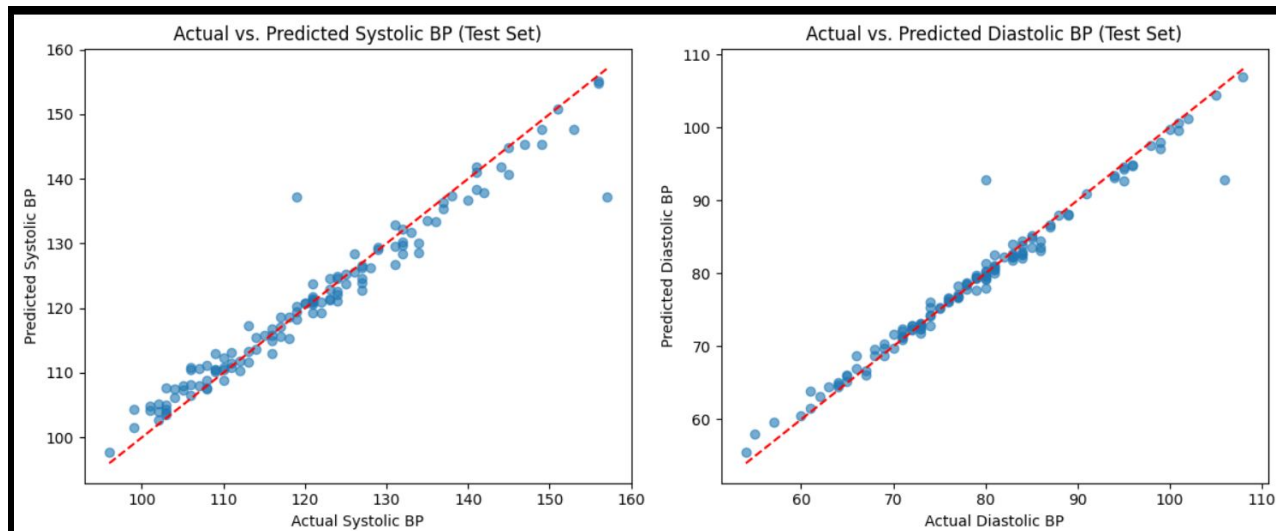
Blood Pressure Model Process

- Capture Frames
- Validate and check for bad data
- Capture rPPG
- Calculate PTT
- Multivariable Regression output
- Feature Importance
 - Weight 0.24
 - Height 0.23
 - BMI 0.21
 - Age 0.17
 - PTT 0.12



Blood Pressure : Diastolic/Systolic Blood Pressure

Model Metrics



- MSE (Systolic BP): 10.72
- MSE (Diastolic BP): 3.87
- R^2 Score (Systolic BP): 0.95
- R^2 Score (Diastolic BP): 0.97
- Systolic BP: MAE 3.27
- Diastolic BP 1.96

Challenges building BP model

- Worked on Three Model Types
 - Physnet
 - DeepPhysnet
 - XGboost
- Tried Synthetic Data

Model Type	Systolic	Diastolic
XGBoost R ² Score	0.95	0.97

Blood Oxygen Saturation (SpO₂)

- **(IDEAL APPROACH)** Remote SpO₂ Estimation:
 - Use RGB or near-infrared (NIR) cameras to analyze the ratio of reflected light from oxygenated and deoxygenated blood.
 - Multispectral analysis (if feasible) for more accurate SpO₂ estimation.
 - Models:
 - Convolutional Neural Networks (CNNs) for pixel-wise classification.
 - Regression models to map spectral data to oxygen saturation levels.

SpO2Model - Using Anomaly Detection (ALTERNATE APPROACH)

1D-PPG signal

- ANOMALY_THRESHOLD = 2.0
- Std deviation threshold for anomaly detection

Preprocessing PPG

- Red x1
- Green x3
- Blue x18
- X: 3 Red – 2 Green
- Y: 1.5 Red + Green -1.5 Blue
- $X - (\sigma X / \sigma Y) * Y$

Anomaly Rate

Epoch 200 – Loss: 73151.1131

Model Save

Anomaly Threshold 635296.9901

3/125 = 2.4%

Please tune in-field and adjust as necessary we have no ground truth

Respiratory Rate

Because of the multivariable, It's not possible to gain isolated MSE R^2

Respiration Rate Actual	Respiration Rate Predicted
85.82	83.8
78.49	80.6
87.64	84.3
87.5	83.37
84.45	83.18

These are actually blood pressure predictions that I have not been able to switch over to the actual Respiratory Rate calculation. But it's an example of the +/- 5% tolerance

During actual inference, I separate the variable, having a prediction of ACTUAL Respiratory Rate: CONTINUED

- Epoch 55/55 Loss 224.76
- Kmeans (n=3) Silhouette Score: .41 (Best Attempt)
- Respiratory reading:
 - Ground Truth: 27.1
 - Predicted Inference: 28.5
- Estimation of Error is +/- 5%.

CONT: Respiratory Rate
Respiratory Metrics

- Thermometer -> temperature
- Weight -> inexpensive digital scale
- Height -> tape measure
- BMI -> recursive calculation
- Vessel Length -> recursive calculation
- Diastolic Blood Pressure
- Systolic Blood Pressure
- Pulse -> Stopwatch
- Respiratory Rate
- Symptoms by text

Total Biometrics Capture in app

This is a design of what parameters we can capture with inexpensive equipment and a cellular phone

WILLIAM'S WORK

Task 3: Model Development

Model Pipeline

Step 1: Video Preprocessing & Face/Hand Detection

- Use **MediaPipe** for tracking
- Apply **Histogram Equalization** & extract **ROI**

Step 2: rPPG Signal Extraction

- Use **CHROM Algorithm** to extract signals
- Apply **Butterworth Filter** for noise reduction

Step 3: Compute Pulse Transit Time (PTT)

- Detect peaks in signals & compute **PTT**

Step 4: Predict BP Using ML

- Train **XGBoost Model** & predict BP

Key Outputs

1. **Extracted rPPG signals** → `face_rppg.npy`, `hand_rppg.npy`
 2. **Computed PTT value** → `ptt_value.npy`
 3. **Predicted BP results** → `predicted_bp_results.csv`
 4. **Final Model Deployment**
 - Converted to **ONNX**
 - Deployed on **Android/iOS** for real-time inference
1. **Next Steps:** Replace step 2 with deep learning models

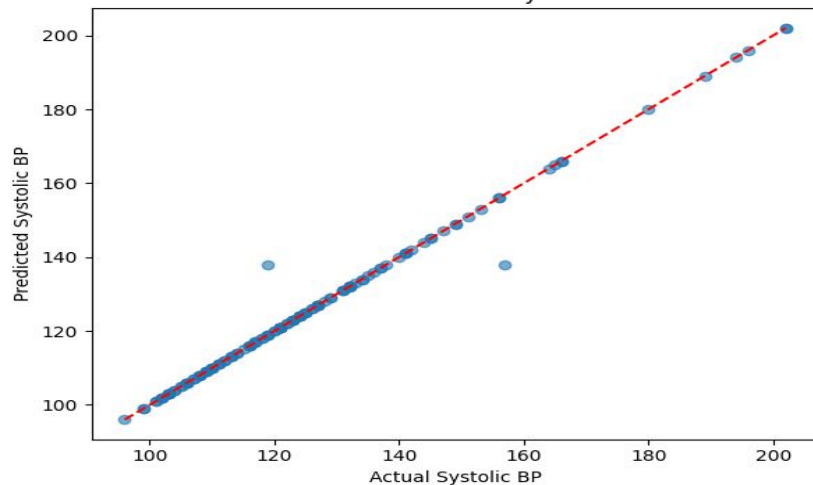
Model Development Cont....



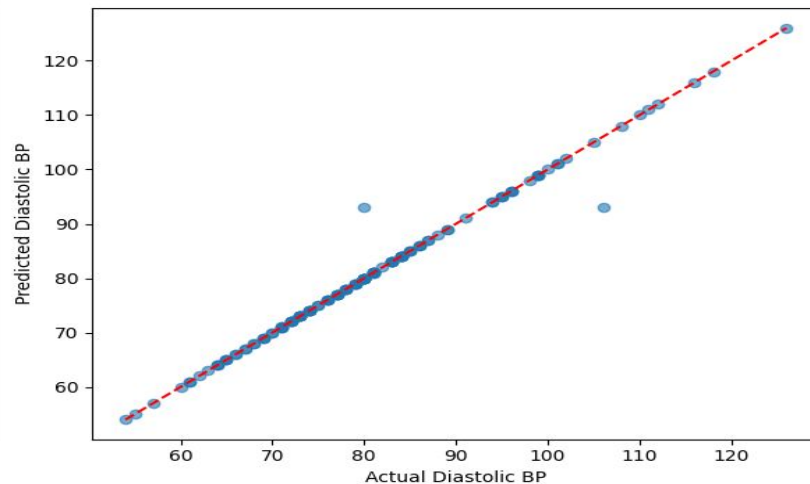
Model Evaluation Metrics

- ◆ MAE (Systolic BP): 0.28
- ◆ MAE (Diastolic BP): 0.19
- ◆ MSE (Systolic BP): 5.27
- ◆ MSE (Diastolic BP): 2.47
- ◆ R^2 Score (Systolic BP): 0.99
- ◆ R^2 Score (Diastolic BP): 0.99

Actual vs. Predicted Systolic BP



Actual vs. Predicted Diastolic BP



User Interface Demo

SOLUTION

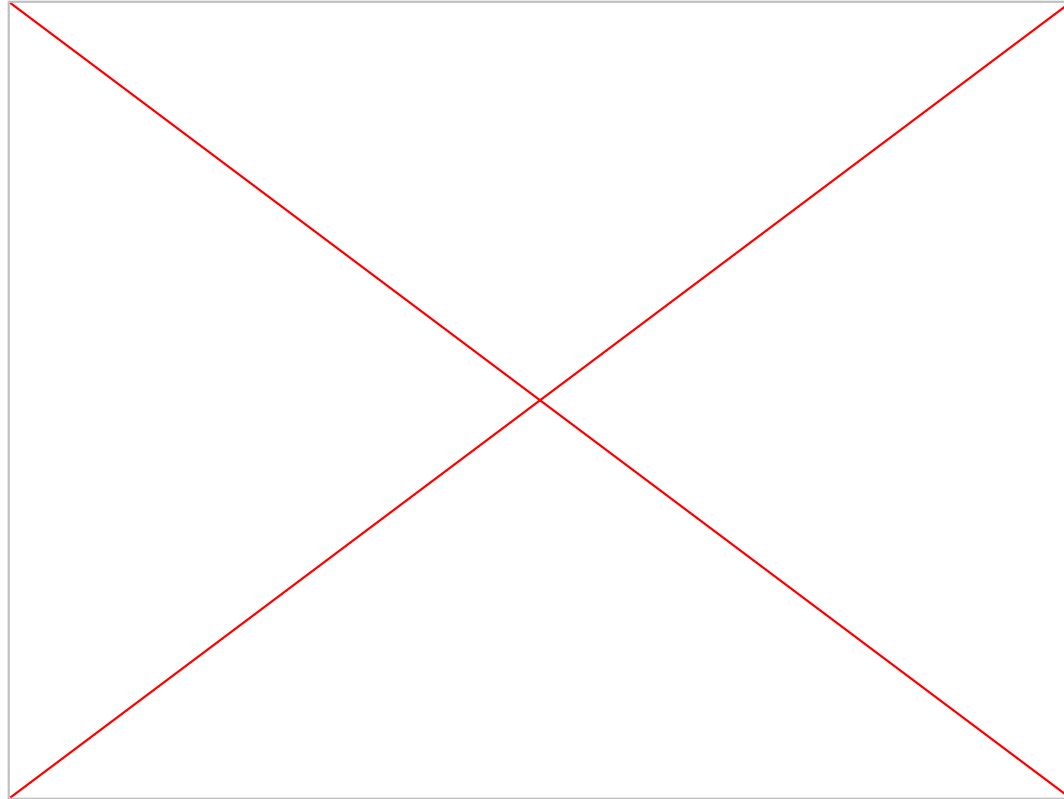
An application using open-source video data to identify the Vital signs of patients in Nigeria



Source: Getty

Demonstration of the earlier demo (has been adjusted for mobile responsive)

This demonstration is very up to date, because of bad calibration on the HR/Respiratory Rate model, it has been delayed and not pushed to production



Project Challenges and Mitigation Strategy

- Lack of commercially licensable datasets
 - Solution: V-BPE dataset which was available was used, synthetic data was also tried
- Staffing availability due to US Election turmoil
 - Forced to change timeline / not make deliverable

Recommendation for Future Development

- Build a labeled dataset of all vital signs using the population of interest, at least a few hundred subjects.
- Retrain the Model pipelines
- Deploy with Android app to portal
- Make cost/benefit analysis of on premise computing vs. cloud.

Thank You