HEART RATE ESTIMATION FROM PPG SIGNALS

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***Abstract*—With the increasing prevalence of smartphones and their enhanced computational capabilities, there is a growing interest in deploying complex tasks on these devices. This paper addresses the challenge of estimating heart rate using smartphones. Traditionally, vital sign estimation algorithms involve multiple pre-processing steps, leading to increased computational complexity and limitations on device compatibility. Leveraging a fully convolutional architecture, our proposed model significantly reduces parameter count, approximately a quarter of conventional architectures employing fully-connected layers for prediction. This not only minimizes the risk of overfitting but also reduces computational complexity. To enhance the model's robustness and applicability, we conducted novel experiments, including the integration of Long Short-Term Memory (LSTM) architecture, training on the BIDMC dataset, and implementing data augmentation techniques. The BIDMC dataset, characterized by its accuracy and substantial data volume, contributes to improved model performance. Additionally, our research introduces a customizable bar graph plotting function for efficient visualization of multiple losses and models. Furthermore, we address the issue of noise in PPG signals by introducing data augmentation, enabling the model to better handle ambient light variations and expanding the dataset with augmented data points. Our proposed LSTM model demonstrates superior convergence speed and comparable performance to previous models. In conclusion, this paper presents an innovative approach to mobile-based heart rate estimation through deep learning, offering a streamlined solution without the need for extensive pre-processing. The provided experimental results, based on a publicly available dataset, showcase state-of-the-art estimation accuracy, making our approach a valuable contribution to the field of non-contact vital sign estimation.**

***Index Terms*—Deep Learning, LSTM, Artificial Intelligence, Computer Vision, Heart-rate Estimation, Vital Signs Estimation, Non-Contact Estimation**

I. Introduction

Regular monitoring of vital signs is essential these days, especially for aging individuals or those with specific medical conditions. The widespread use of smartphones, equipped with advanced hardware and software capabilities, offers a promising opportunity for precise estimation and monitoring of vital signs with near-clinical accuracy [2]. Heart rate (HR) and oxygen saturation level (SpO2) emerge as pivotal vital signs. HR, indicative of one's physiological state, holds great importance in healthcare, while SpO2, measuring blood oxygen levels, plays a crucial role in identifying potential health risks such as respiratory diseases and COVID-19 [3].

For optical estimation of vital signs, Photoplethysmography (PPG) signals serve as a key component. PPG, an uncomplicated and cost-effective optical method, utilizes a light source and a photodetector on the skin surface to gauge variations in blood circulation. Leveraging smartphones with cameras and flashlights, PPG signals can be effortlessly captured by placing a finger over the camera with the flashlight activated. Existing methods for HR and SpO2 estimation encompass a spectrum from signal processing algorithms to deep learning approaches. However, these methods often entail multiple pre-processing stages or demand substantial computational resources, limiting their deployment on mid-range or low-end smartphones [4].

This article introduces novel architectures tailored for real-time heart rate estimation on mobile devices, with the versatility to extend to SpO2 determination. We also introduced an LSTM module for faster convergence and comparable accuracy. These architectures embrace an end-to-end paradigm, obviating the need for pre-processing steps and facilitating seamless deployment on mobile devices. Our fully convolutional architectures, diverging from prior designs with dense connections post-feature extraction, not only reduce parameters but also enhance accuracy. We use the MTHS public dataset of smartphone videos, featuring PPG signals from 62 patients alongside corresponding ground truth HRs and SpO2s. We also compare this performance with the existing BIDMC dataset. While the primary focus is on heart rate estimation, our methods and code demonstrate adaptability for SpO2 determination. Section IV provides in-depth details about the dataset.

We will finally compare the performances of all the deep-learning and LSTM models on different loss functions and check the estimated vs ground truth heart rate comparison and comment on the convergence of different models.

II. Related Work

Several approaches have been explored for heart rate estimation from PPG signals captured in smartphone videos, each presenting unique methodologies and considerations.

In the work by [8], a convolutional-based neural network processes PPG signals from smartphone videos. Initial preprocessing involves converting input videos into three-channel 1D signals, representing the mean values of the frames' red, green, and blue channels. This method employs multiple handcrafted preprocessing steps, including denoising, moving average application, and PCA. Notably, it employs fully connected layers post-convolution, leading to increased network parameters and a higher risk of overfitting compared to newer fully convolutional architectures.

[9] takes a different approach by estimating heart rate through the Fast Fourier Transform (FFT) of single-channel time-series PPG, combined with 3-axis accelerometer motion signals. The resulting four-channel signals undergo processing with an 8-channel 1D convolution-max pool layer and a fully connected network. While effective, the authors acknowledge potential improvement through the utilization of fully convolutional architecture, particularly when incorporating all PPG channels.

In [10], an end-to-end deep learning model is proposed for wrist-worn device-based heart rate estimation. Distinguished by its elimination of pre-processing steps and motion data reliance, the model processes eight consecutive one-second PPG data segments through parallel convolutional and LSTM layers. The feature vectors produced are concatenated and further processed through additional LSTM layers, concluding with a linear layer predicting heart rate. Despite its advantage in eliminating pre-processing steps, the presence of LSTM layers contributes to a relatively high computational complexity.

Our Contribution:

Building upon the existing literature in [1], our work, introduces innovative enhancements for heart rate estimation using PPG signals from smartphone videos. Our proposed model incorporates LSTM architecture, adapts to the BIDMC dataset for improved accuracy, introduces a customizable bar graph plotting function for visualizing multiple losses and models, and explores the use of data augmentation for robustness against ambient light variations. By addressing these aspects, our approach aims to advance the state-of-the-art in mobile-based heart rate estimation. Our work also highlights the convergence rate of models with different architectures and loss functions.

III. Problem Definition

The problem addressed in this project is to develop models for accurate and real-time heart rate estimation from Photoplethysmography (PPG) signals obtained through smartphone-captured videos and evaluate them on different loss functions by comparing them with the ground truths, with a comparison of evaluations on different datasets.

The task involves converting visual information from these videos into meaningful physiological metrics, specifically heart rate. The inputs are video data captured by smartphone cameras, through which the PPG signal metrics are obtained, and the output is an estimated heart rate. This problem is of significant importance as it enables non-invasive health monitoring, especially for individuals with specific medical conditions or the elderly. The ability to derive vital signs from readily available smartphone data enhances accessibility to healthcare information and facilitates timely interventions.

IV. Algorithms Used

We present a highly efficient real-time algorithm for the concurrent estimation of heart rate (HR) on smartphones and mobile devices. Our innovative deep-learning approach significantly reduces the number of parameters compared to prior vital sign estimation architectures. Notably, it eliminates the necessity for any pre-processing steps on the input photoplethysmography (PPG) signal.

When provided with an image sequence or video captured from fingertips, our method performs real-time estimation of HR. The architecture adopts a fully convolutional approach, leading to a network with four times fewer parameters than conventional methods employing a fully connected network post-convolution. This reduction in parameters diminishes the risk of overfitting, which is especially advantageous for smaller datasets. To further streamline computational complexity, we forego the use of commonly applied batch normalization layers.

Crucially, our proposed architecture obviates the need for implementing handcrafted stages such as the design and application of bandpass filters. This not only enhances efficiency but also simplifies the overall algorithmic process. The architecture, as illustrated in Figure 1, provides versatility and adaptability to different scenarios and input variations.

A. Dataloader

In the data loader phase, the preprocessing steps are initiated to ready the photoplethysmography (PPG) data for model training. Firstly, the PPG input is created, considering either the red channel exclusively or all three channels. Subsequently, the data is downsampled to 15 Hz using a specified downsample factor, which is set at 2 for the MTHS dataset and 8 for the BIDMC dataset, resulting in 15 samples per second. The downsampled data is then divided into sequences, each spanning 10 seconds of signals, corresponding to 150 samples. The target variable, either heart rate (HR) or oxygen saturation (SpO2), is concurrently created. For each 10-second sequence, a single output is generated, representing the average heart rate for that specific duration, translating 150 input samples to one output heartbeat. The dataset is further partitioned into training, validation, and test sets, with an 80% allocation for training, 15% of training data for validation, and 20% for testing. Ultimately, the data loader returns the sets required for both PPG input and the respective target variable, facilitating the subsequent training and evaluation processes of the machine learning model.

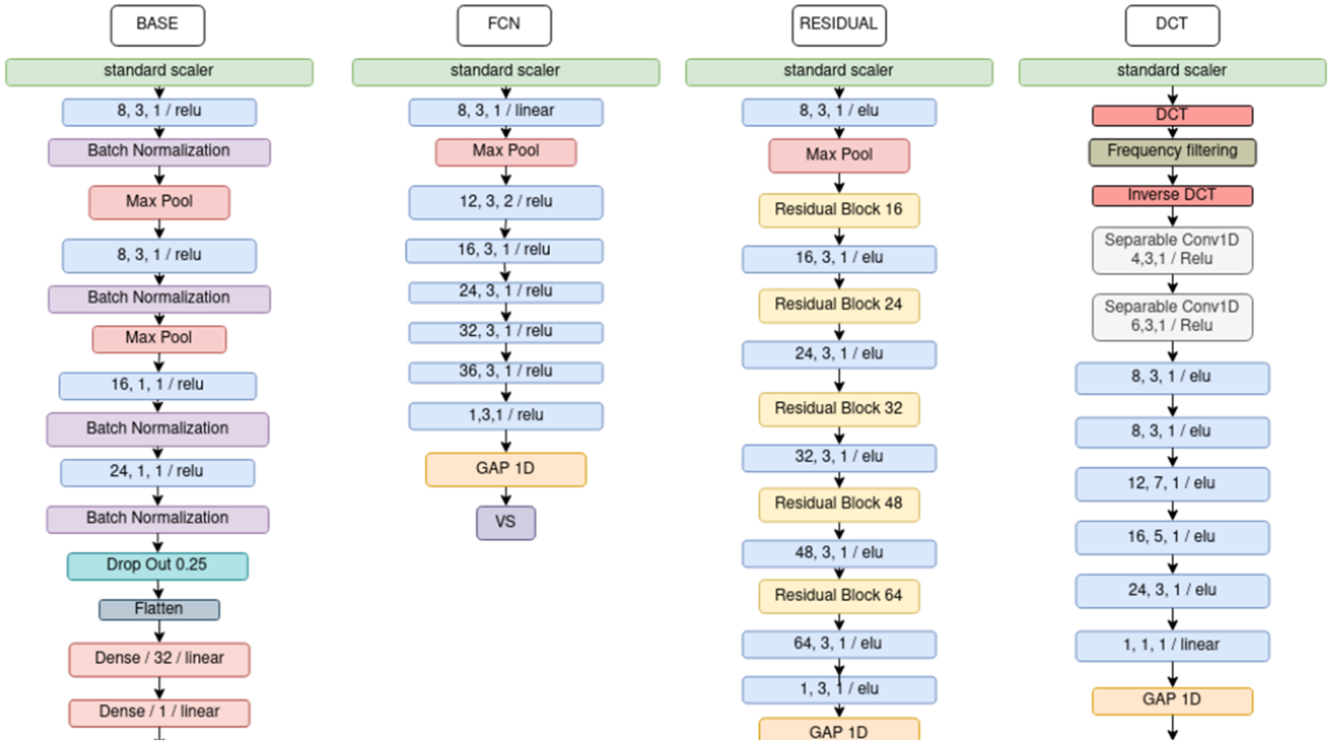


Fig. 1: The proposed architectures for vital sign estimation, there are five different architectures provided.The fifth model is LSTM.

B. Model Architectures Used

The goal of the models is to identify complex patterns so that they can be effectively predicted or classified. Each design provides different approaches to handling and processing temporal sequences. These architectures include the Base Model, FCN(Fully Convolutional Network), FCN with Residual Connections (FCNResidual), FCN with Discrete Cosine Transform (FCNDCT), and an LSTM Model.

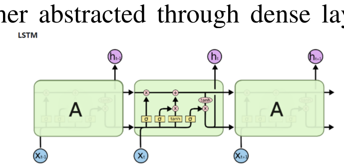
A basic structure is established by the Base Model, which consists of successive Conv1D layers with conventional scaling and subsequent convolutional procedures with different filter sizes and activations. Through the use of convolutional operations and feature stabilization approaches, this model aims to capture important temporal aspects and spatial patterns. The architecture reaches a linear output layer at the end of a sequence of dense layers enabling higher-level abstraction.

The Fully Convolutional Network (FCN) model, in comparison, places more emphasis on a deeper stack of Conv1D layers with various activations and filter sizes. In order to condense spatial information, it also includes global average pooling. A single-node output layer comes next. Through intensive convolutional processes, this design seeks to utilise hierarchical structures present in the temporal sequences.

By incorporating residual connections between Conv1D layers, the FCN with Residual Connections (FCNResidual) enhances the FCN design. This model mitigates vanishing gradient problems and improves feature learning depth by encouraging straight pathways for gradient flow. It proceeds similarly, with a single-node output layer, global average pooling, and Conv1D layers.

By applying a Discrete Cosine Transform to the input sequences before passing them through a series of Conv1D and SeparableConv1D layers, the FCN with Discrete Cosine Transform (FCNDCT) offers a unique method. The objective of this modification is to extract crucial frequency-based features that could be important for the prediction challenge.

Last but not least, the Long Short-Term Memory (LSTM) layers used in the LSTM Model are excellent at capturing temporal dependencies within sequences. This architecture uses numerous LSTM layers with dropout for regularisation after initial preprocessing with Conv1D layers. The output is flattened and then further abstracted through dense layers to provide a linear output.



Every model architecture has distinct qualities of its own, providing varying trade-offs between temporal context awareness, feature extraction capabilities, and computational complexity. Specific use cases, data properties, and the intended balance between interpretability and predictive performance all influence the architectural decision. Together, these models offer a full range of methods for reliable temporal sequence analysis when combined with oxygen saturation and heart rate information.

C. Loss Functions Used

We evaluate the performances of each of the proposed models on four loss functions. In machine learning, various loss functions are employed to quantify the disparity between predicted and actual values during model training. One commonly used metric is the **Mean Squared Error (MSE)**, expressed as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

. Another metric, the **Mean Absolute Error (MAE)**, measures the average absolute difference between predicted and actual values and is given by

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

. The **Huber Loss** combines aspects of MSE and MAE, presenting a more robust solution to outliers:

$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{for } |y - f(x)| \le \delta \\ \delta|y - f(x)| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}$$

. Lastly, the **Log Cosh Loss** provides MSE-like behavior but is less influenced by occasional wildly incorrect predictions:

$$LogCosh(y, f(x)) = \log(\cosh(y - f(x)))$$

. These loss functions provide a comprehensive comparison of the models, and we can determine the best model by training all models on all these losses and evaluating test data using MAE as a common metric for comparing losses.

V. Datasets

BIDMC Dataset: The BIDMC dataset presents a rich resource extracted from critically-ill patients undergoing hospital care at the Beth Israel Deaconess Medical Centre in Boston, MA, USA. This dataset captures detailed physiological signals, including photoplethysmogram (PPG), impedance respiratory signal, and electrocardiogram (ECG), sampled at a rate of 125 Hz. The recordings, each spanning eight minutes, provide a comprehensive view of the patients' physiological responses. What sets BIDMC apart is the inclusion of ground truth data for essential parameters such as heart rate (HR), respiratory rate (RR), and blood oxygen saturation level (SpO2), sampled at a frequency of 1 Hz

MTHS Dataset: MTHS dataset is a novel collection from 62 patients (35 men and 27 women) designed for smartphone-based vital sign estimation. The dataset features PPG signals obtained at 30 FPS using the RGB camera of an iPhone 5s. The ground truth data includes HR and SpO2 levels sampled at 1 Hz, acquired through a pulse oximeter (M70). The PPG recordings involve keeping the flashlight on during the data collection phase, with patients instructed to fully cover the

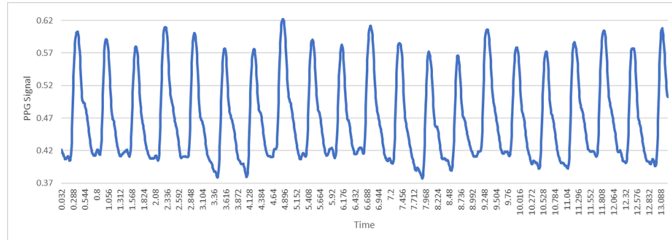


Fig. 2: A 13 second PPG sample from BIDMC dataset

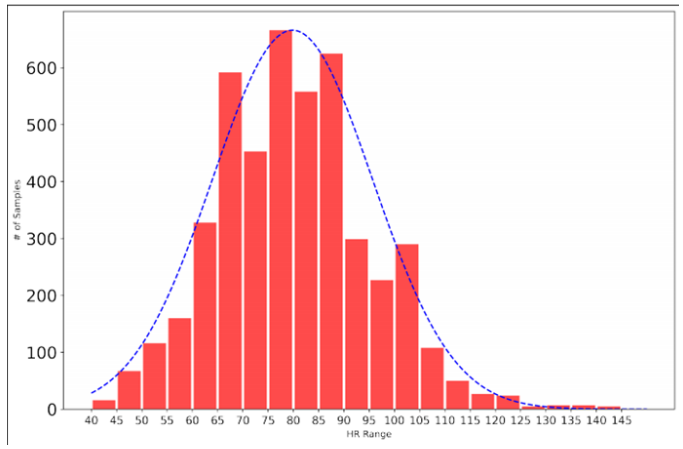


Fig. 3: Heart Rate distribution for MTHS dataset

camera and flashlight with their fingertips. This unique dataset is publicly available on Github, addressing the gap in publicly accessible datasets with smartphone-acquired PPG signals.

The 30 FPS rate of PPG signal implies a sampling rate of 30 Hz which leads to 1800 PPG samples for 60 seconds. The vitals are measured at 1 Hz and thus, for 60 seconds, we have 60 samples.

VI. Experimental Results

Five different models i.e. the base model, the FCN model, the FCN model with residual connections called FCN_residual

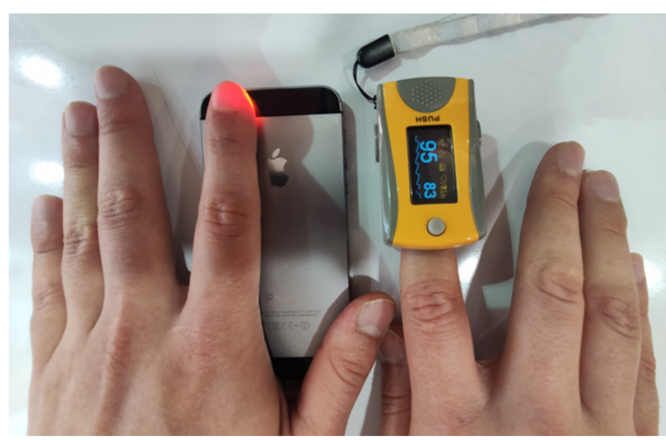
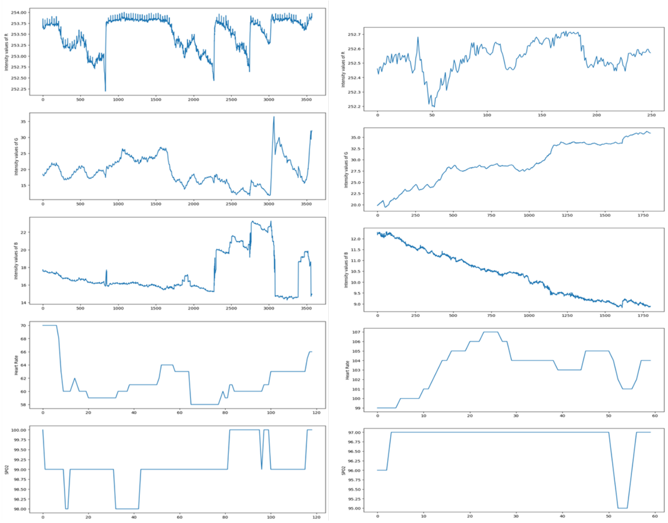


Fig. 4: Setup for MTHS dataset collection



(a) Patient ID 23 (b) Patient ID 50

Fig. 5: Two MTHS dataset samples with RGB channels, Heart Rate and SPO2 levels.

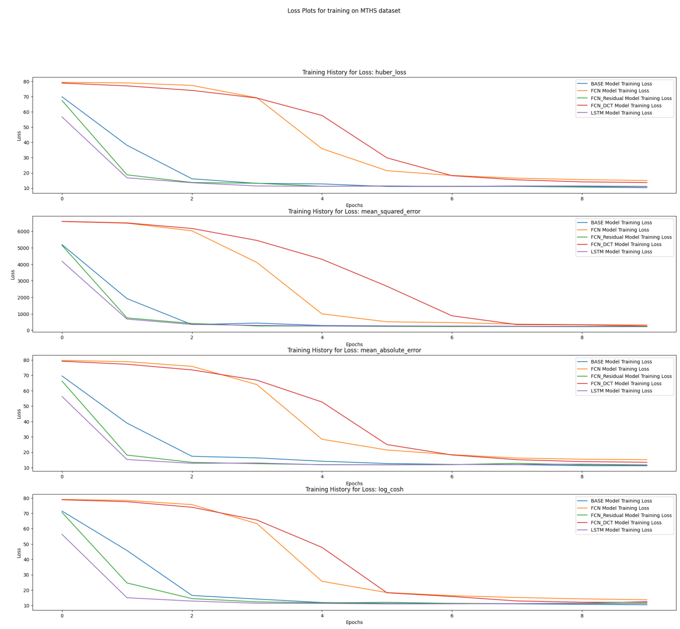


Fig. 6: Convergence of Models on MTHS Dataset

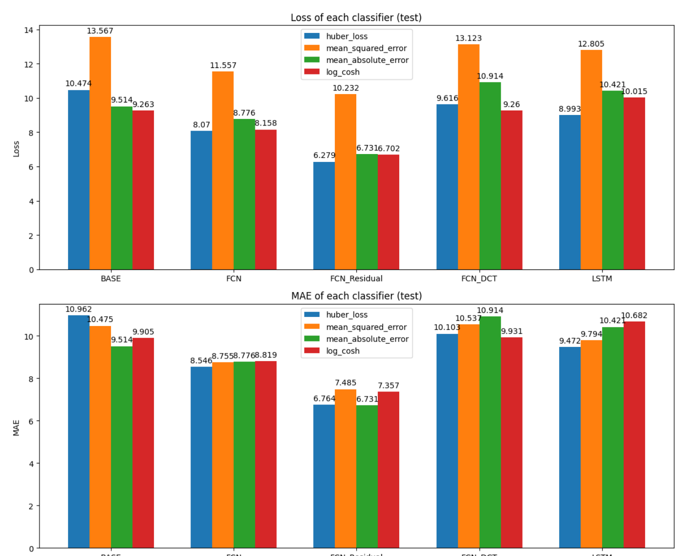


Fig. 7: Performance of Models on MTHS Dataset

model, the FCN model using the Discrete Cosine Transform called FCN_DCT model and the LSTM model were used for performance evaluation. Each model's performance was evaluated using four different loss functions- Huber loss, Mean-sqaured error, Mean-absolute error and Log cosh. h. The mentioned networks are trained for 125 epochs on two datasets, including BIDMC [15] and our MTHS dataset. FCN_residual was found to be the best model (i.e. gave the lowest error) and Huber loss was found to be the best loss. Their combination gave a training loss of **6.279**, which was observed to be the lowest among all the combinations.

A. Training Loss on MTHS

The LSTM model displays a notable advantage in terms of faster convergence when compared to other models within the ensemble. This faster convergence contributes to saving computational time and resources during the training process. The LSTM's ability to capture temporal dependencies efficiently enables it to converge quicker, thereby reducing the computational burden and training duration. On the other hand, the FCN with residual connections (FCN-Residual) exhibits a compelling characteristic of achieving lower loss after a substantial number of epochs. Despite initially trailing behind in convergence speed compared to the LSTM, the FCN-Residual gradually demonstrates superior performance with reduced loss, highlighting its potential for capturing more intricate patterns and enhancing predictive accuracy over an extended training period. This trade-off between convergence speed and ultimate performance showcases the varying strengths and capabilities of these models, offering valuable insights into their suitability for different applications and datasets.

B. Experimental Results on MTHS

In our study, the FCN Residual model emerged as the most effective in predicting the target variable compared to the alternative models. The FCN Residual model likely leverages residual connections, which capture the difference between predicted and actual values. This architectural choice often enhances the model's ability to learn complex patterns and contributes to improved predictive performance. The term "Residual" implies that the model's architecture involves the use of residual learning, a technique that aids in mitigating issues related to vanishing gradients and accelerates the training of deep neural networks.

Additionally, our experimentation with various loss functions revealed that Huber loss consistently delivered the best performance across a majority of the models, showcasing

Loss \model	BASE	FCN	FCT resid-ual	FCT DCT	LSTM
Huber loss	10.47	8.07	6.28	9.61	8.9
MSE	13.56	11.55	10.23	13.12	12.8
MAE	9.51	8.77	6.73	10.91	10.42
Log cosh	9.26	8.15	6.70	9.26	10.01

Fig. 8: Losses of different Models on MTHS Dataset

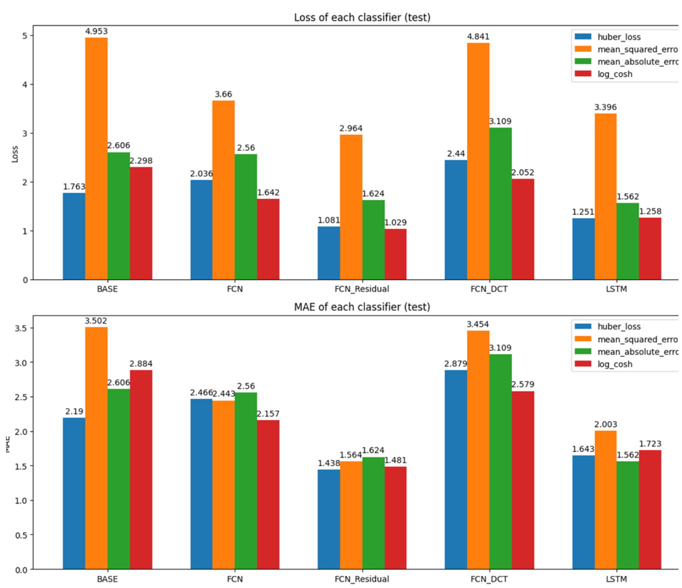


Fig. 9: Performance of Models on BIDMC Dataset

its robustness. Huber loss combines characteristics of both Mean Squared Error (MSE) and Mean Absolute Error (MAE), offering a balanced compromise that is less sensitive to outliers compared to MSE. This makes Huber loss particularly valuable when dealing with datasets that may contain noisy or irregular data points.

In conclusion, the FCN Residual model excelled in predicting the target variable, and Huber loss proved to be a robust choice for most models, with the exception of the specified base model. These findings contribute valuable insights into the model selection and optimization processes in the context of our study.

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Fig. 10: Losses of different Models on BIDMC Dataset

C. *Experimental Results on BIDMC*

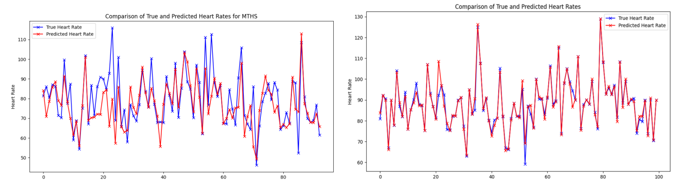
In our analysis, we noted that the loss values obtained from training models on the BIDMC dataset were consistently lower when compared to those from the MTHS dataset. This discrepancy in loss values prompted an investigation into the underlying factors contributing to this difference.

Upon closer examination, we found that the BIDMC dataset exhibited superior performance, yielding lower loss values during training. This enhanced performance can be attributed to the robust methodology employed in acquiring the BIDMC dataset. The methodology adopted for data collection in the BIDMC dataset is characterized by a higher degree of accuracy in capturing physiological signals. Additionally, the BIDMC dataset contains a more extensive set of data points, facilitated by the prolonged duration of each reading. The increased number of data points contributes to a richer and more comprehensive dataset, providing the models with a more diverse range of examples to learn from.

In summary, the observed improvement in performance on the BIDMC dataset can be linked to both the enhanced accuracy in data acquisition methodology and the larger volume of data points. These factors collectively contribute to a more effective training environment, resulting in lower loss values and, consequently, a more refined and accurate model.

D. *Comparison with ground truth*

The comparison plots between ground truth and predicted heart rate offer a visual assessment of model performance on different datasets, namely BIDMC and MTHS. Notably, the model trained on the BIDMC dataset consistently exhibits superior accuracy, evident in the closer alignment of predicted values with the ground truth. This suggests that the BIDMC dataset, likely due to its larger size and specific characteristics, facilitates better model generalization. Conversely, the MTHS-trained model may show a larger variance, indicating potential challenges in data distribution or quality. In essence,



(a) MTHS Dataset (b) BIDMC Dataset

Fig. 11: Comparison of ground truths from the predicted heart rates.

these plots emphasize the critical role of dataset selection in achieving accurate model predictions.

VII. Future Work

In the domain of unsupervised learning, a series of experiments was conducted, revealing less-than-satisfactory performance. Despite the acknowledged advantages of fully convolutional structures in terms of reduced parameters and enhanced performance compared to models with fully connected prediction heads, the higher Floating Point Operations per Second (FLOPs) required by FCN models pose a challenge. The scarcity of both high-quality and diverse data for smartphone-based vital sign estimation opens up a promising avenue for future exploration of unsupervised learning methods in this field.

Looking ahead, the potential for further research involves the collection of SpO2 and HR data from individuals with respiratory-related diseases, thereby diversifying the dataset beyond its current focus on healthy subjects. Additionally, an intriguing prospect lies in exploring the application of transformer-based models for training PPG signals. Transformers, known for their success in various domains, present an opportunity to augment the adaptability and performance of vital sign estimation models. Further investigation into these directions could contribute to advancements in smartphone-based healthcare technologies.

VIII. Conclusions

In this paper, we have presented a comprehensive analysis of heart rate estimation from PPG signals using deep learning techniques on smartphone-based platforms. Our approach leveraged fully convolutional architectures and LSTM models, demonstrating effective performance with reduced computational complexity. The experiments conducted on the BIDMC and MTHS datasets revealed insights into the impact of dataset selection and model architecture on prediction accuracy. Our work indicates that such models have significant potential for real-time, non-invasive, and accessible health monitoring using everyday devices like smartphones. Future research could focus on expanding the dataset diversity, exploring transformer-based models, and optimizing the balance between model complexity and performance.

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