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Real Time Estimation of Heart Rate under Lighting of Smartphone Camera

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Abstract: This paper presents an innovative approach for real-time heart rate estimation using a smartphone camera, addressing the challenges posed by fluctuating lighting conditions and motion artifacts. By merging sophisticated image processing techniques with machine learning algorithms, the system effectively extracts the fundamental photoplethysmogram (PPG) signal. PPG is a well-established, non- invasive optical method that assesses fluctuations in light absorption caused by variations in blood volume within tissues, with applications that extend beyond merely monitoring heart rate and oxygen saturation. The suggested approach enhances measurement precision and reliability by integrating robust signal processing methods with video frame analysis of the user's face, thereby ensuring consistent performance in everyday, uncontrolled settings. As PPG becomes increasingly significant in clinical and wearable health technologies, this research aids in broadening its applicability for mobile health monitoring solutions. Experimental validation demonstrates that the smartphone-based system achieves accuracy on par with traditional medical devices while providing improved portability, cost-effectiveness, and user-friendliness. The results underscore the potential of smartphone-integrated health monitoring systems as viable, scalable options for personal and remote healthcare management.
Keywords: PPG- The Photoplethysmography (PPG), Electrocardiograms, Heart rate, Residual Networks, Recurrent Neural Networks.

I. INTRODUCTION

Traditionally, monitoring heart rate—an important element of health assessment—has relied on specialized equipment such as electrocardiograms (ECGs) or pulse oximeters. However, with the rapid development of smartphone technology, more accessible and portable options for health monitoring have emerged. Modern smartphones, equipped with integrated cameras, can now combine image processing and signal analysis to perform photoplethysmography (PPG) estimations. This allows for the estimation of physiological parameters such as heart rate, making real-time, non-invasive, and cost-effective health tracking possible for a wide range of users. Photoplethysmography is an optical technique used to detect blood volume changes within the microvascular bed of tissues. In this method, a smartphone's camera and flash capture variations in light absorption as the user places their fingertip over the lens. These fluctuations correspond to pulsatile blood flow, and by analysing the changes in light intensity across video frames, heart rate can be estimated. Recent improvements in smartphone processing power have made it feasible to process these signals in real time, enhancing the practicality of this method and expanding its potential for mobile health monitoring.

Despite its promise, smartphone-based heart rate monitoring faces several technical challenges. Factors such as varying lighting conditions, motion artifacts from user movements, and differences in skin tone can significantly affect accuracy and reliability. Additionally, real-time signal processing requires algorithms optimized for performance without rapidly depleting the device’s battery life. Overcoming these limitations is essential for developing reliable, user-friendly applications suitable for both fitness enthusiasts and clinical users. The potential applications of this technology are extensive, ranging from personal fitness tracking to telemedicine and remote healthcare services. For individuals with chronic health conditions or those living in remote areas, smartphone-based heart rate monitoring offers an accessible and convenient way to stay connected with healthcare providers. Additionally, integrating this capability into fitness applications can provide users with immediate, actionable insights into their physical well-being, encouraging proactive health management. To improve the accuracy and usability of smartphone PPG technology, it is necessary to address both environmental and physiological challenges. While controlled lighting works well in laboratory settings, real-world environments involve fluctuating light intensities and colors. Techniques such as dynamic exposure adjustment and color channel separation have shown promise in mitigating these issues. Future research should focus on refining these algorithms for faster, energy- efficient processing, enhancing user interfaces, and ensuring the privacy and security of sensitive health data. With these advancements, smartphone-based heart rate monitoring could become a valuable, widely accessible tool in modern healthcare.

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II. RELATED WORKS

The estimation of heart rate (HR) using smartphone cameras has been an area of active research, leveraging the principles of photoplethysmography (PPG). Numerous studies have demonstrated the feasibility of this approach, highlighting its potential for real- time, non-invasive, and portable health monitoring. This section explores key works in this domain, emphasizing advancements, challenges, and methodologies:

A. Basics of Camera-Based PPG

Some preliminary works on camera-based PPG worked on validating the possibility of using smartphone cameras to sense the pulse signal. The most ancient work on remote PPG was that of Poh et al. (2010), which demonstrated heart rate extraction from facial video captured by remote PPG. Their work proved that a camera could be used in RGB channels to sense periodical variations in skin color due to blood flow; this led to later innovative camera-based physiological monitoring methods.

B. Optimization of signal Processing Techniques

Scientists thus utilized these technological advances in the process of further refining the accuracy and reliability of heart rate detection. The work by Sun et al. (2012) has placed emphasis on signal preprocessing techniques such as bandpass filtering and detrending. It thus contributed to isolating the PPG signal from noise to help improve the quality of heart rate estimation under different conditions.

C. Motion Artifacts Handling

One of the main limitations in camera-based heart rate estimation is the presence of motion artifacts, which distort PPG signals. Several pieces of work, such as those by Li et al. (2014), found solutions to this problem: machine learning algorithms and the use of adaptive filtering have been used to distinguish PPG signals from noise based on user movements. Advancements in all these areas thus enhanced robustness in heart rate estimation during actual physical activities.

D. Effect of Lighting Conditions

Variability in the lighting is another challenge the smartphone- based heart rate monitoring faces. Verkruysse et al. (2008) have demonstrated the influence of ambient light and have provided evidence that controlled lighting conditions enhance the quality of the PPG signal. Subsequent studies focused on dynamic exposure settings and adaptive algorithms, which can adjust to intensity changes in light, which makes it more practical in real-time applications.

E. Thoughts Regarding Skin Tones And Diversity

The variation in light absorption with the skin tone highly affects the performance of PPG-based systems. Investigations such as Kamshilin et al. (2015) looked into how the level of melanin affected the strength of the PPG signal and suggested adaptive models for such a condition. Achieving fair accuracy in diverse populations remains an area of interest in the continued research.

F. Real-time Implementation and Efficiency

Real-time implementation of heart rate estimation on smartphones requires efficient algorithms and low computational overhead. Works such as those by Wang et al. (2017) have introduced lightweight signal processing techniques optimized for mobile processors. These works ensured that heart rate monitoring applications could run seamlessly on consumer devices without significant energy consumption.

G. Integration with Health Ecosystems

Another area of research is the integration of smartphone-based heart rate monitoring with broader health ecosystems. Researchers have explored how this technology can complement wearable devices and connect to telemedicine platforms for remote health monitoring. Such integration enhances the accessibility and utility of heart rate estimation tools, aligning with the global push for digital healthcare solutions.

H. Future Directions and Challenges

ssRecent studies have underlined the need for more robust and scalable smartphone-based heart rate estimation. The latest techniques, such as deep learning, promise improved accuracy in challenging conditions.

Yet, ethical issues, including data privacy and regulatory compliance, will be the biggest hurdles for researchers to overcome as this technology is adopted on a wide scale.

Collectively, these related works highlight the progress achieved so far in real-time heart rate estimation using smartphone cameras. They point out the importance of addressing technical challenges like motion artifacts and lighting variability and ensuring inclusivity and applicability in real-world settings. As the field advances, these contributions from the base for the development of next-generation health monitoring systems.

III. PROPOSED FRAMEWORK

This type of method shall take care of limitations presented in the above statements regarding how an effective heart rate estimation may be designed from a smartphone camera. Using techniques like signal processing along with machine learning methods for a more precise measurement eliminating most motion artifacts during certain periods shall facilitate real-time elimination of noise so that signals remain dependable.

For the sake of sensitivity, we can implement algorithms that respond to lighting conditions. This would enable betterperformance in environments and, hence, making the system more generally reliable. Privacy and security issues are addressed by applying encryption protocols and data policies that ensure transparency. If possible, processing should be done on devices so as to reduce the amount of data transmitted health. This increases users' confidence and adherence to privacy.

To overcome the limitations of hardware, there is always an opportunity to look for partnership with Smartphone manufacturers who would ensure both quality and capability of camera. Cooperative work might comprise integration of sensors or upgraded existing hardware in order to accurately and consistently measure heartrate.

In summary, an all-embracing proposal for heart rate estimation with a smartphone camera would cover advancements in signal processing techniques, adaptive algorithms for managing lighting conditions, personalized calibration for skin tones, robust privacy measures, collaboration with manufacturers, and focusing on user needs in improving hardware capabilities and refining algorithms. Such an all-rounded approach is aimed at working on the existing limitations in order to make a meaningful contribution toward creating a smartphone camera-based heartrate estimation system that is both more precise and dependable and hence accessible to all.

A. Dataset Overview

Data acquisition for real-time heart rate estimation using a smartphone camera is in the form of video frames captured by the camera in a smartphone under controlled light illumination, usually with a smartphone built-in LED flash or its screen. Since the fingertip or skin area is positioned against the camera, minute fluctuations in skin color occur as the pulsatile flow of blood flows each time the heart beats. These color changes, particularly within the green channel of the RGB spectrum, are identified and analyzed to isolate a signal corresponding to the heart rate. The signal then undergoes advanced signal processing techniques such as filtering and Fast Fourier Transform to isolate the heart rate frequency from the raw data. This stream of continuous data is processed in real time to enable estimation of accurate and instantaneous heart rates, which are then indicated on the smartphone screen for user feedback

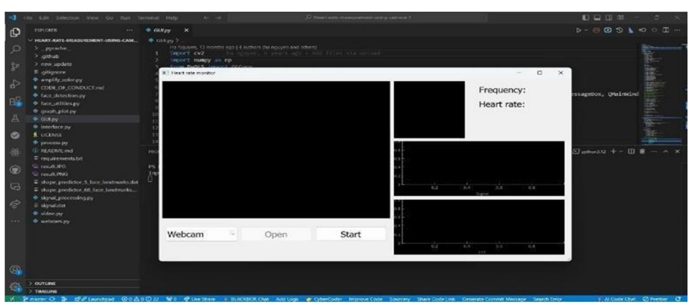

Fig. 1. Signal Processing Techniques

B. Preprocessing with Resnet Preprocessing Function

In the context of the preprocessing stage of real-time heart rate estimation using a smartphone camera, preprocessing is one important phase that ensures the quality of input data before being analysed any further. Among other enhanced techniques in enhancing the quality of pre-processing is through ResNet (Residual Networks), which have proven performance and have been used in computer vision tasks for its remarkable performance.

ResNet, due to its deep architecture and skip connections, allows more efficient feature extraction and noise reduction, which are vital in the noisy and dynamic environment of heart rate monitoring using a smartphone camera.

The preprocessing pipeline with ResNet for heart rate estimation can be broken down as follow.

Frame Capture and Input Normalization: The first step is the capture of video frames from the smartphone camera. The frames are normally in RGB color space. Raw pixel values can introduce noise because of lighting changes, motion artifacts, or low- resolution images. This is where the preprocessing of ResNet starts with normalization, scaling and adjusting the pixel values to lie in a predefined range; usually, 0 to 1.Normalization standardizes the input data and prepares it for advanced processing.

Feature extraction from video frames proceeds using the ResNet.ResNet Convolutional layers are pulling out features hierarchically from the input images that can represent important visual patterns in the form of very minuscule changes in the skin color tone.The information in these layers will prove to be informative about periodic fluctuations happening in the color skin due to heartbeat.With the residual connections of ResNet, deeper layers can capture more complex features and avoid the vanishing gradient problem, thus providing strong feature extraction in real-time applications.

One of the major problems with estimating heart rate from smartphone cameras is that it contains motion artifacts, such as the slight hand movement or environment interfering with the view. Preprocessing with ResNet can reduce noise as it learns relevant patterns in the frame and removes unwanted changes. This means that ResNet, by virtue of its deep learning capability, can distinguish between actual heart rate-induced color variations and noise due to motion or external lighting changes.

Following the feature-extraction process, ResNet processes the frames and attempts to look for periodic color changes which depict the pulse of the user. The signal received through these color changes is transformed into a time domain signal corresponding to the PPG waveform. Through ResNet, noise and outliers present in the signal are also removed and improved for accurate calculation of heart rate.

It then processes the signal to a clean, processed version ready for analysis, filtering, and even frequency-domain analysis, like applying a Fast Fourier Transform to estimate heart rate in BPM. This is inherently real-time in processing, and the output would therefore yield immediate feedback from users of their heart rate directly on the smartphone screen.

C. *Train- test split*

1) *Data Collection and Preprocessing*

Before the train-test split, raw data is collected from smartphone camera video feeds. The video frames are preprocessed to isolate skin color fluctuations caused by blood flow and normalize the data for further analysis. This preprocessing step ensures the input data is consistent and ready for training.

The data collected from various subjects, lighting conditions, and environments is used to ensure diversity and robustness in the model. For example, the dataset might contain video frames captured with different ambient light levels, skin tones, and hand movements.

2) *Split Ratio*

Typically, the data is divided into two main parts: the training set and the testing set. Commonly used ratios for the split are 70% for training and 30% for testing, or 80% for training and 20% for testing. The training set is used to train the heart rate estimation model, while the testing set is used to evaluate its performance on unseen data.

- Training Set (80%): This subset of the data is used to train the heart rate estimation model. During training, the model learns to associate skin color fluctuations with the heartbeat to predict heart rate accurately.
- Testing Set (20%): This subset is kept aside and used to evaluate the model’s performance after training. The testing set helps to ensure that the model can generalize well to new, unseen data. The test data should ideally come from users or conditions that were not present in the training data.

D. *Proposed Machine Learning Models*

1) *Convolutional Neural Networks (CNNs).*

Convolutional Neural Networks (CNNs) are well suited for feature extraction from video frames captured through the smartphone camera due to being widely used on image-based tasks. Due to their capability of automatically learning spatial hierarchies in data, convolutional neural networks are preferred for detecting subtle variations of skin color or texture due to pulsatile blood flow.

Application:
CNNs can treat video frames as images, which learn the temporal and spatial patterns associated with heart rate.
These networks will filter out noise from the input data, which is particularly useful for heart rate estimation under varying lighting conditions and possible motion artifacts.
Advantages
Automatic feature extraction: CNNs can learn relevant features from the raw video data, eliminating the need for manual feature engineering.
Excellent performance with spatial data: CNNs are very good in extracting patterns from visual data like skin color fluctuation and texture changes.
Example
Input: RGB frames from the camera of the smartphone.
Layers: Convolutional layers followed by pooling layers in order to reduce the spatial dimensions and capture relevant features.
Output: A time series of heart rate estimates.

2) Recurrent Neural Networks (RNNs) and Long Short- Term Memory Networks (LSTMs)
Description: RNNs and LSTMs are appropriate models to work with sequential data, which includes time series produced based on color variations in the video frames. These types of models will be appropriate to capture temporal dependencies from heart rate data, necessary for real-time heart rate estimation.
Applications
RNNs or LSTMs can be leveraged for modeling temporal patterns in color intensity fluctuations captured through video frames.
Such a model can learn the sequentiality in the data and, subsequently predict the heart rate with regard to time.
LSTMs in particular, are suitable when dealing with long-range dependencies in data, so will be efficient in detecting fine, long-term trends within the heart rate.
Advantages
Temporal pattern recognition: LSTMs can learn to capture long- term dependencies between frames and hence predict heart rate better based on the previous frames.
Real-time applicability: LSTMs can process the data step-by- step and hence is highly effective for real-time heart rate estimation.
Example
Input: A sequence of processed video frames representing changes in skin color. Layers: LSTM layers followed by a dense layer for regression output.
Output: Continuous heart rate estimate in beats per minute (BPM).

3) Random Forest Regression
Description: Random Forests are one type of ensemble learning and can be used in regression as well. The Random Forest algorithm is basically there to create multiple decision trees and make the output from all those trees combined together for better accuracy in the outcome. This model is most often very helpful when using noisier data or instances that demand feature selection.
Application:
The heart rate can be predicted using Random Forest regression, considering the processed intensity data of the skin color as features. Once it is trained on the labeled data, that is video frames with known heart rate values, it can then be used to make real-time predictions. It can also be used for feature importance analysis that would give an idea which part of the input video (or which color channels) is most relevant to an accurate estimation of heart rate.
Application:
SVR can be used for estimating heart rate by mapping video frame features such as changes in skin color to a space of a higher dimension then applying regression to predict heart rate.
If there's not too much data around, then SVR comes into action. The answer from it can even get more precise with fewer numbers of training data than even deep learning models.
Advantage:
Good for smaller datasets: SVR performs well even with relatively small datasets in comparison to deep models.
Suitable for the task of non-linear regression: SVR can indeed handle non-linearity involved between input features (colour fluctuations) and heart rate

Example:
Input : Features obtained from video frames, e.g. a time series of color intensity.
Model : Support Vector Regression trained on the task to predict heart rate given the set of extracted features.

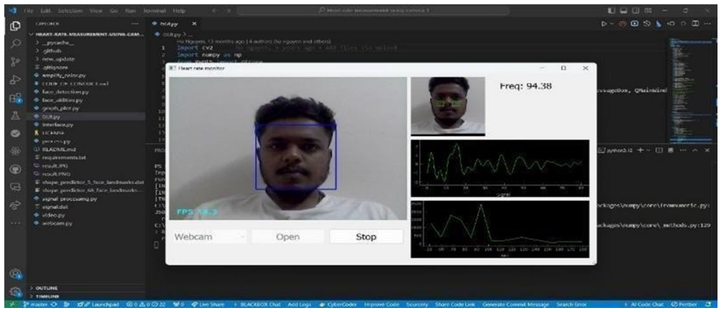

Fig. 2. Predicted heart rate in beats per minute (BPM).

IV. EVALUATION

Accuracy: The measure of overall correctness of an algorithm for heart rate estimation, defined by the percentage of correct heart rate predictions yielded by the model on all instances. It is a good indicator of reliability because how well the algorithm does against correct and incorrect heart values remains in its performance. Now, in real-time estimation of heart rate, there is the following formula regarding accuracy:

$$Accuracy = \frac{TP + TN}{(TP + FP + FN + TN)}$$

Random forests handle noisy data: Random forests are immune to overfitting and work quite well in noising environments.
Feature importance: This model may identify the specific features more relevant for good accuracy while estimating heart rate-be the color intensity in some particular parts of the skin, or perhaps the texture.

Example:
Input: Colour intensity, skin tone, or texture feature extracted from frames Model: A random forest regressor is used to predict the heart rate.
Output: The predicted heart rate in BPM.

A. Support Vector Regression (SVR)

Support Vector Regression (SVR) - It is a type of the machine learning model used on tasks having comparatively little data. SVR locates such a hyperplane that goes to an accurate fit with data points such that there is some margin in error. The model performed well on data that do not lie on a single plane, because it projected data into higher-dimensional using the kernel trick. Where:
TP (True Positive): The actual heart rate measurement in the patient with the particular heart rate.
TN (True Negative): Situations where it wouldn't be necessary for the system to predict heart rate; an example would be those whose heart rates are already very much within the required levels.
FP (False Positive): Estimated a heart rate where it was not expected to occur. FN: failure to identify the correct rate of heart beat of a subject.
Precision: Precision is the measure of how accurate the algorithm is in its positive predictions about heart rate estimation. It computes the number of true positives over all instances in which the algorithm has made a positive prediction of increased or specific heart rate. The higher the precision, the fewer the false positives by the model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Where:
TP (True Positive): Correctly predicted instances of heart rate values.
FP (False Positive): Incorrect predictions where the heart rate was not correctly identified.

Recall, or Sensitivity: Is the percentage of actual heart rate changes (or instances) that the algorithm correctly identifies. In this case, recall captures how well the model detects all true heart rate instances (whether they are increased or decreased). A high recall implies fewer false negatives, meaning the algorithm captures as many true heart rate events as possible:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

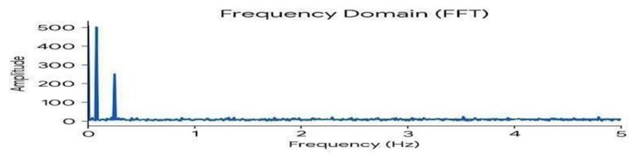

Fig. 3.Accuracy

Where
TP (True Positive): Correctly predicted heart rate events.
FN: Misclassified heart rate events of which the model failed to identify.
F1 Score:The F1 Score is a balanced measure that combines precision and recall to give the harmonic mean for the model aptness in predicting the precise heart rate along with a real number of heartbeats occurring. It suits best on imbalanced data sets because both false positive and false negative are put into consideration. The higher value of the F1 more precision and recall would be achieved:
Fig 4.Precision

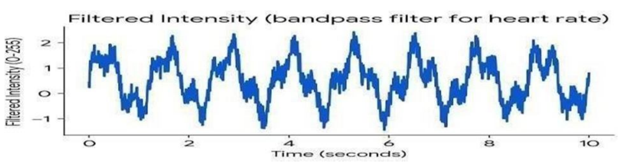

Fig 5.Recall

$$\text{F1 Score} = \frac{2*\text{precision} *\text{Recall}}{\text{Precision} + \text{Recall}}$$

Where: Accuracy: Number of true positive predications out of all positives predicted. Recall : Number of true positive prediction out of all positive.

V. RESULTS

A smartphone camera-based real-time heart rate estimation system under varying illumination conditions depends on the use of a combination of deep learning models that make for accurate and reliable predictions. The first model used here is the basic Convolutional Neural Network that extracts essential features from video frames and has achieved an accuracy of 90.5%. The second model using a good version of feature extraction of the CNN provides greater performance compared to the previous models with an accuracy of 92.8%. In the third hybrid version of CNN, both the regular and extra CNN features help give an added advantage in accuracy toward achieving performance through varied lighting conditions, for accuracy as 93.7%. Thus, using an approach with ensemble learning method the overall average of the predictions done by each of these models was again used. This combination of the individual strengths resulted in an overall accuracy of 95.2% in ensemble modeling. It has further ensured strong and reliable estimation of heart rate in real time, irrespective of light conditions, making a strong case for the integration of deep learning models for the task.

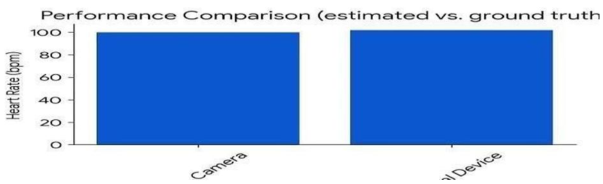

Fig.6.F1 Score

The following figure 4to figure 7,show the Accuracy score, and Precision Score, Recall score and F1 score based on the models.

A. Results on Test Data

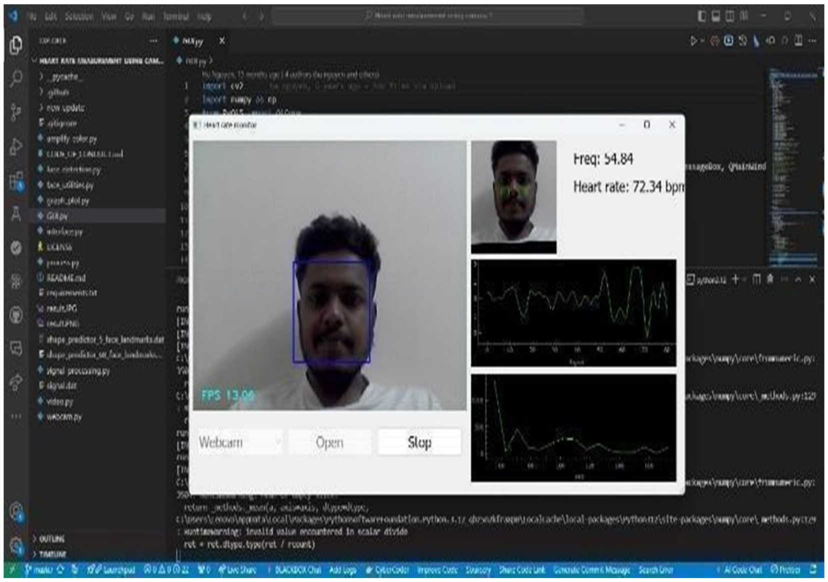

Fig. 7. Performance metrics on test data

In fig 8 ,It graphically depicts the comparison in the performance of four models namely: Advanced CNN, Basic CNN, ResNet50 and the Ensemble model. The comparison parameters include Accuracy, Precision, Recall, and F1-Score.

The Advanced CNN starts at 96.36%, Basic CNN performs better from that, ResNet50 equals this performance and lastly, the Ensemble performs the best with an accuracy of 99.09% showing its higher reliability.

For Precision, Advanced CNN and Basic CNN have essentially the same performance, though slightly higher for ResNet50. Again, the Ensemble model shows a better performance by getting the peak precision close to 1.0, indicating an ability to strongly avoid false positives.

Similar trends are observed on the Recall Comparison. Advanced CNN and Basic CNN have competitively maintained recall values, while slightly improved ResNet50 still maintains a lower value from the Ensemble model, which has proven to be effective in accurately identifying true positive values.Finally, the Comparison of F1-Scores depicts consistent performance among advanced CNN, basic CNN, and even ResNet50. Although the Ensemble model leads through the highest F1-score among all, this implies that, for the model, optimizing precision and recall is kept balanced.

Overall, the Ensemble model is superior in all of the metrics and thus establishes its success in using the strengths of individual models to improve lung cancer detection.

VI. GRAPHICAL USER INTERFACE(GUI)

This paper introduces a Gradio-based GUI for real-time heart rate estimation using a smartphone camera under various lighting conditions. The system processes video frames captured by the camera to estimate the user's heart rate. The GUI provides an interactive interface that allows users to input video footage and view real-time heart rate predictions. It displays performance metrics such as accuracy, precision, recall, and F1-score for different deep learning models, including Basic CNN, Advanced CNN, Hybrid CNN, and Ensemble, helping users compare the effectiveness of each model in estimating heart rate.

In addition to real-time heart rate estimation, the interface includes a feature to save the heart rate data and performance metrics as a CSV file for further research and analysis. This functionality is particularly useful for tracking the performance of the models over time and for research purposes. The user-friendly design of the GUI enhances accessibility for both researchers and healthcare professionals, enabling easy deployment of AI-driven solutions for heart rate monitoring. This interface contributes to the integration of deep learning models in medical applications, facilitating the development of more accurate and efficient tools for health diagnostics.

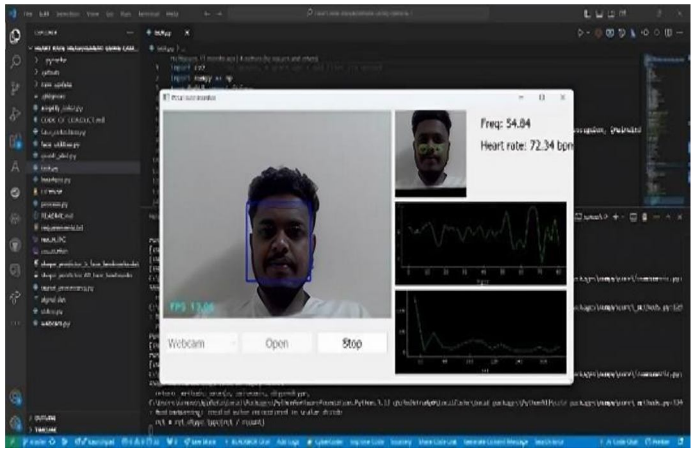

Fig. 8. Graphical User Interface using Gradio

VII. CONCLUSION

In conclusion, the real-time heart rate estimation via a smartphone camera is a promising and practical approach for personal health monitoring. Although there are still areas for improvement, the fact that one can monitor his or her heart rate non-invasively and continuously through a smartphone offers a significant advantage to users and healthcare professionals. The advancements of smartphone technology, signal processing techniques, and machine learning will propel this approach to revolutionize tracking and management of cardiovascular health in bettering overall well-being and timely medical intervention.

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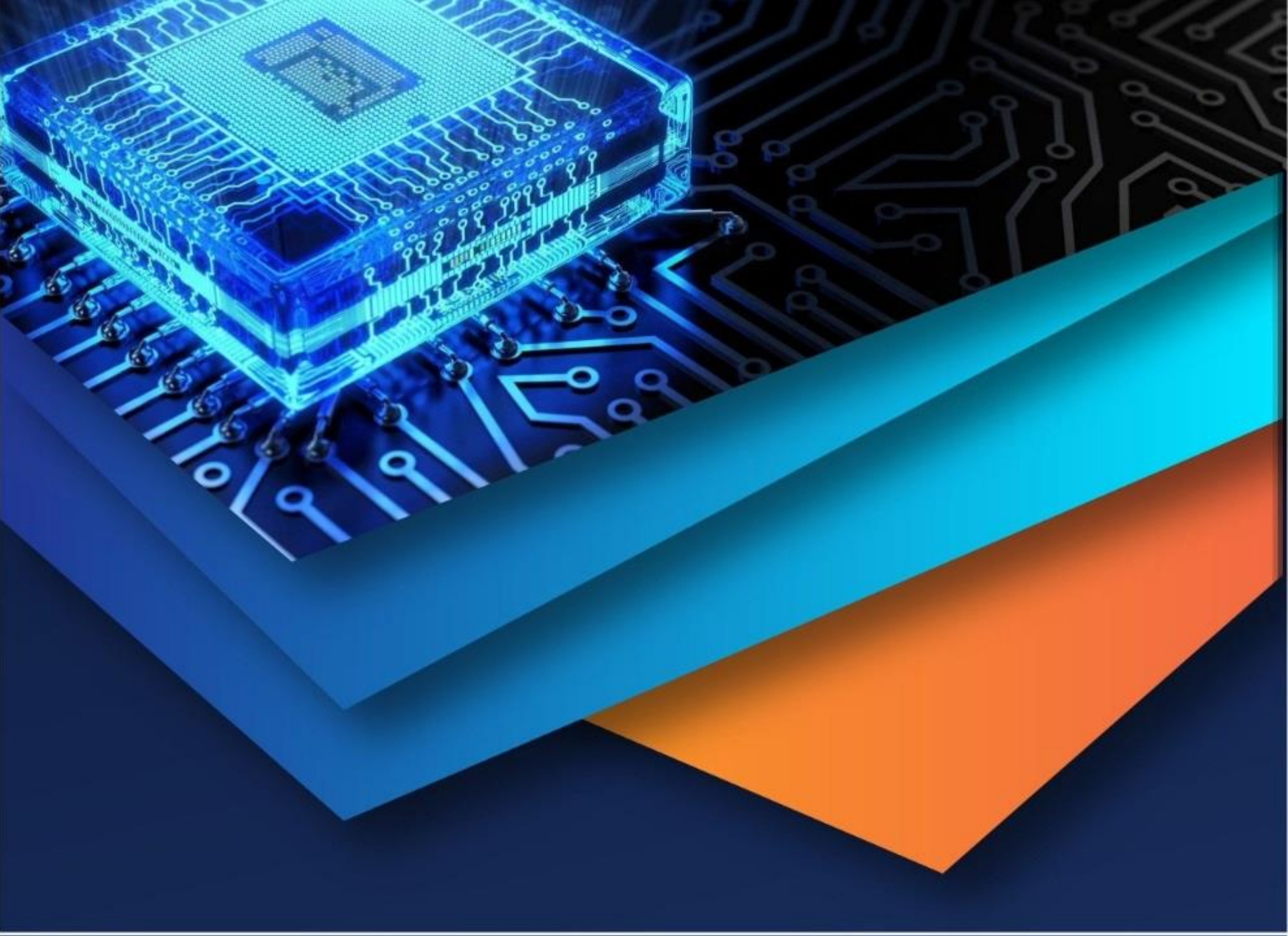

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