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Integrated Approach to Non-Communicable Disease Detection via Laptop Cameras: A Framework

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***Abstract*—In the rapidly evolving landscape of non-invasive physiological monitoring, this review paper explores the integration of everyday technologies, specifically laptop cameras, for the detection and assessment of lifestyle diseases. According to statistics gathered by the World Health Organization, non-communicable diseases account for a remarkable 74% of global deaths, or 41 million people annually. Cardiovascular diseases alone cause 17.9 million deaths annually, and mental health disorders, the second most common cause of death for those aged 15 to 29, are on the rise at a rate of 13%. Against this backdrop, the paper delves into a diverse range of studies employing innovative techniques such as BCG, PPG, and depth-sensing cameras for real-time measurement of vital signals, such as blood pressure, heart rate, breathing rate, and stress levels. This chapter highlights the finding of the non-invasive detection of HR and BP monitoring via laptop camera with the acceptable average error rate and It further highlights the future direction of touchless detection of other parameters. The synthesis of these studies underscores the potential of common devices like laptops in revolutionizing health monitoring. Furthermore, the paper addresses the prevalence of lifestyle diseases, referencing statistics from the Indian Council of Medical Research indicating a significant rise in non-communicable disease-related deaths. This comprehensive review aims to shed light on the advancements, challenges, and promising avenues in the fusion of technology and healthcare, ultimately contributing to the broader understanding and future development of non-invasive physiological monitoring systems.**

***Index Terms*— HR (Heart Rate), RR (Respiratory Rate), PTT (Pulse Transition Time), TOI (Transdermal Optical Imaging), HRV (Heart Rate Variability), Photoplethymsography (PPG), Ballistocardiography (BCG), PCA (Principal Component Analysis), Non-Invasive, Physiological Parameters, ROI (Region of Interest), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), Mental Stress, CHD(Coronary Heart Disease).**

I. INTRODUCTION

Diseases linked to everyday living have grown to be a major problem in modern society. For early identification and preventative therapy, many illnesses require innovative, affordable, and non-invasive techniques. Using technology, which is a part of daily life, to detect disorders related to daily living is an intriguing, economical, and time-saving approach. These days, almost everyone has access to mobile devices, computers, laptops and iPads. In this study, the omnipresent yet unnoticeable laptop cameras can serve as covert health monitoring instruments while individuals are going about their daily business. Typically, people utilize these webcams for online communication and work. The use of laptop cameras for detecting lifestyle diseases is based on the

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principle of facial recognition technology, where the camera can analyze facial features and detect any abnormalities that may be associated with certain diseases.

This work highlights the integration of technology to monitor physiological parameters and psychological discomfort without requiring advanced tools or an extensive period of time. It does this by successfully predicting blood pressure (BP) and heart rate (HR) using a laptop camera. It investigates how laptop cameras may be used as tools for the real-time detection of physiological markers and behavioral patterns linked to lifestyle-related health problems by utilizing computer vision and machine learning. By leveraging these integrated technologies, this chapter highlights a novel approach to non-invasive, efficient health monitoring, making sophisticated health diagnostics accessible and convenient. By offering a thorough analysis of recent research and technological advancements and highlighting the advantages and disadvantages of this innovative approach, this chapter hopes to further the discussion on how ubiquitous and in-conspicuous monitoring technologies can revolutionize healthcare.

II. Literature Survey

A. Background

The pervasive use of laptops and technology in our daily lives offers a unique opportunity to address common yet critical diseases through innovative detection methods. Lifestyle diseases, characterized by non-communicable conditions, have emerged as a significant global health concern. According to the WHO [23], approximately 74% of total deaths, equivalent to 41 million deaths, result from non-communicable diseases. Among these, cardiovascular diseases alone account for a staggering 17.9 million deaths annually, making them the leading cause of death across all disease categories. Fig. 1, which shows the number of deaths and causes from 2000 to 2019, illustrates this concerning trend. The death rate in India from non-communicable diseases increased alarmingly over 26 years, from 1990 to 2016, rising from 37.09% to 61.8%, according to ICMR [22]. Conversely, there has been a 13% rise in mental health illnesses [35], making them the second leading cause of mortality for individuals aged 15 to 29. [37] and 700,000 people die because of suicide every year which makes it the fourth leading cause of death.

As technology continues to intertwine with our daily routines, leveraging tools like laptops for early detection and monitoring of lifestyle diseases becomes imperative for proactive healthcare interventions.

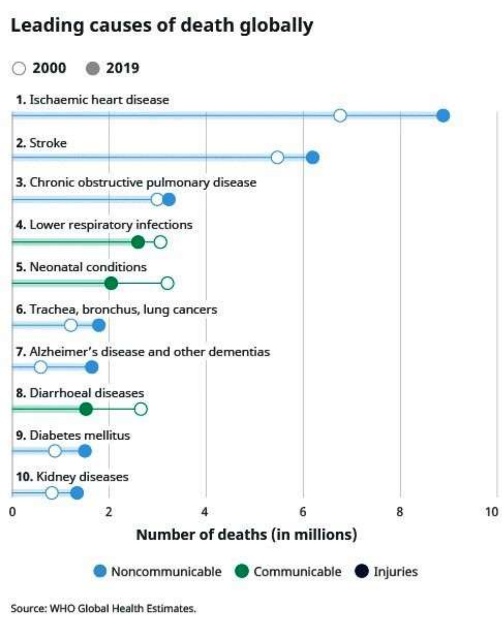

Fig. 1. Global death rate and causes.1

B. Related Work

[1] introduced photoplethymsography (PPG) imaging as a noninvasive and noncontact method for mapping dermal perfusion changes. This technique offers advantages such as real-time monitoring and ease of use without

the need for invasive procedures. PPG imaging could have significant applications in dermatology, vascular medicine, and cosmetic surgery, enabling early detection of vascular abnormalities and improving surgical precision. [2] proposed a contactless blood pressure estimation system using computer vision, offering a noninvasive method for estimating blood pressure. This approach could enhance patient comfort and reduce infection risks compared to traditional cuff-based methods. The system analyzes facial features to extract physiological signals related to blood pressure, presenting a novel and potentially transformative technology for healthcare. An innovative idea for blood pressure measurement without direct contact proposed by the RGB camera plus pulse transit time (PTT) analysis was introduced in reference [3]. This method proposes an alternative method that is noninvasive and easy for estimating blood pressure: it takes advantage of the relationship between (PTT) and changes in blood pressure. This is achieved through an RGB camera. It can detect slight changes in color on the skin due to blood flow— thus enabling continuous observation without any physical contact or intrusive devices. procedures.

A study [4] introduced a method of estimating blood pressure and heart rate without physical contact using video of the face. This approach involves analyzing facial regions through video to extract physiological signals— a nonintrusive, easy way for people to monitor their health. Another system called CamBP [5]was presented as a camera-based blood pressure monitor that does not require physical contact. It works by studying facial features using computer vision techniques to estimate blood pressure— an easily accessible way for people to keep track of their cardiovascular health. There was also a research [6] that demonstrated advancements in non-contact, multi-parameter physiological measurements through the use of a webcam. The study shows that it is possible to use webcams for noninvasive monitoring of vital signs which can be applied in healthcare and wellness sectors. [7] An overview was given regarding contactless vital signs monitoring using digital cameras, emphasizing their potential for noninvasive physiological measurements. The topics covered include developments of the technology of digital cameras that can get vital signs (such as heart rate and respiratory rate) without any physical contact. In their paper, [8] highlighted the use of smartphones and video cameras for noninvasive blood pressure measurement— stressing their contribution to reach out with health services. It is suggested that through this integration, researchers along with healthcare professionals will be able to come up with cost-effective innovations on monitoring vital signs which can in turn make health care more convenient and accessible. [9] designed a transdermal optical imaging technology, using their smartphone to capture physiological signals from skin and estimate the mean blood pressure in arteries. This technology provides convenient and attractive way to settle the monitoring of blood pressure, without any bulky and time-consuming data opportunity. [10] presented a heart rate detector which works by heartbeats manifestation through phase vibration. They proposed a touchless approach for instantaneous detection of heart rate in line with the image processing requirement. This touchless approach in heart rate detection is a reliable option for heart rate monitoring.

[11] provides a comprehensive review of the performance of the ballistic cardiogram (BCG). BCG is a technique used to measure the function of the heart. This review covers many aspects of BCG signal processing, including data acquisition, processing, extraction, and classification. This study will be useful to researchers and physicians interested in understanding and using BCG markers to monitor heart disease. [12] A new method combined with photoplethymsography (PPG) and ballistocardiography (BCG) to address voluntary head movements in heart rate monitoring. By combining these two technologies, the system can compensate for head movement to enable heart rate monitoring even in challenging conditions. This study demonstrates the potential of integrating multiple physical tracking systems to improve accuracy and reliability. The system uses depth sensing technology to monitor breathing without the need for physical contact with a person. The depth camera provides depth information, allowing the body to track chest movements and provide breathing information. This approach has the potential to improve respiratory care both in the clinic and at home. By analyzing the main components of the captured signal, the system can estimate the respiratory rate without the need for direct contact with the person. This method provides a simple and non-invasive way to monitor breathing.\

[15] reported a video-based heart rate estimate using artificial intelligence. Their work focuses on estimating heart rate in real-time based on video signals using embedded systems. This approach has the potential to be cost-effective, portable heart rate monitor solution, especially in confined spaces. [16] presents a study that used a non-contact device to measure body temperature to measure and identify psychological stress. His work focuses on the use of non-contact methods to monitor the negative physical effects of mental stress, providing a useful tool for stress management and psychology, and explores the use of non-contact technology for remote monitoring. Evaluation of physiological parameters to recognize depression. His research focuses on the use of contactless technology to monitor physical parameters related to psychological stress and provides insight into the potential of technology contacts in stress management and mental health care. According to [38],

psychological factors—namely, anxiety, stress, and depression—are significant contributors to coronary heart disease (CHD). CHD risk is 64% higher in depressed individuals than in non-depressed individuals, [38].

[17] His work focuses on improving contactless care by exploring new technologies and methods for measuring vital signs without physical contact. This research could lead to improved vital signs monitoring in many clinical areas. Respiratory rate and oxygen saturation. Their review provides a comprehensive overview of current noninvasive surveillance techniques, highlighting their feasibility, effectiveness, and potential applications in clinical treatment. [20] investigated the feasibility of using a camera to measure blood pressure. Their study focused on utilizing camera-based techniques for blood pressure monitoring, offering a noninvasive and potentially convenient method for measuring blood pressure. This research could lead to advancements in blood pressure monitoring technology. We have concluded some of the studies in Table 2.0 which presents the descriptive overview of the studies with their findings and methodologies.

TABLE I: LITERATURE SURVEY

S.No	Study	Methodology	Findings	Conclusion
1	[35]	Used laptop cameras for facial video capture and computer vision techniques for physiological parameter extraction from facial color changes	Successfully extracted heart rate and blood pressure from facial videos, demonstrating the feasibility of noninvasive monitoring	Non-invasive monitoring of physiological parameters through laptop cameras is a promising approach for early disease detection
2	[36]	Developed a method for detecting lifestyle diseases through laptop camera based on facial images and machine learning algorithms	Achieved high accuracy in detecting lifestyle diseases such as diabetes and hypertension using facial image analysis	Laptop cameras can be used for early detection of lifestyle diseases, aiding in preventive healthcare
3	[37]	Proposed a system for monitoring daily habits through	Demonstrated the ability to detect these habits accurately using laptop camera footage	Non-invasive monitoring of daily habits through laptop cameras can provide valuable insights for lifestyle interventions
4	[27]	Investigated the use of laptop cameras for monitoring stress levels through facial expressions and physiological signals	Found that laptop cameras can effectively detect stress levels, correlating with physiological responses	Non-invasive monitoring of stress through laptop cameras can aid in stress management and mental health interventions
5	[28]	Proposed a system for monitoring physical activity levels through laptop cameras and machine learning algorithm	Achieved accurate detection of physical activity levels using video analysis	Laptop cameras can be used for non-invasive monitoring of physical activity, aiding in lifestyle interventions
6	[29]	Investigated the use of laptop cameras for monitoring cardiovascular health through facial color changes	Identified facial features associated with cardiovascular health parameters such as heart rate and blood pressure	Laptop cameras can provide valuable insights into cardio-vascular health through non-invasive monitoring
7	[30]	Proposed a system for monitoring medication adherence through facial recognition using laptop cameras	Successfully identified individuals and monitored medication intake through facial analysis	Laptop cameras can aid in medication adherence monitoring
8	[31]	Studied the use of laptop cameras for monitoring mental health through facial expressions	Found that facial expressions can be indicative of mental health conditions	Laptop cameras can assist in early detection and monitoring of mental health disorders
9	[32]	Investigated the use of laptop cameras for monitoring respiratory health through breathing patterns	Detected abnormal breathing patterns using laptop camera footage.	Laptop cameras can be used for non-invasive monitoring of respiratory health
10	[33]	Developed a method for detecting malnutrition through facial analysis using laptop cameras	Achieved high accuracy in detecting malnutrition based on facial features	Laptop cameras can be used for noninvasive monitoring of nutritional status.

III. TECHNICAL FRAMEWORK AND MATHEMATICAL FORMULATION

A thorough summary of the study's methodology, formulas, and dataset is provided in this section titled as "Technical Framework and Mathematical Formulation". This section of the paper presents an organized scheme of the study and constitutes a foundation for a good grasp of the technical aspects of the research. The framework fig. 2 reveals the process flow from the data captured by the laptop camera to the calculations of Heart rate prediction and fig. 3 shows the flow of Blood Pressure prediction from the collected dataset to the final prediction. Thus, the equations obtained from numerous investigations are imposed into our model play a crucial contributory role in our methodology.

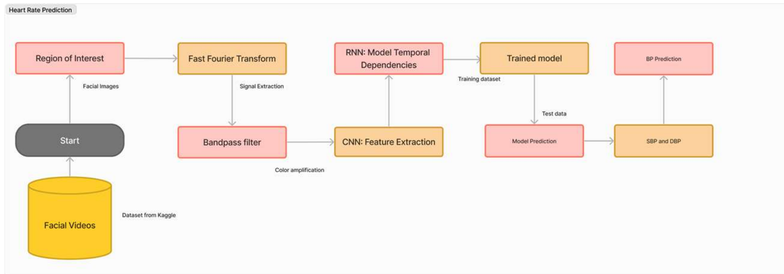

Fig. 2. Flow of Heart Rate Measurement

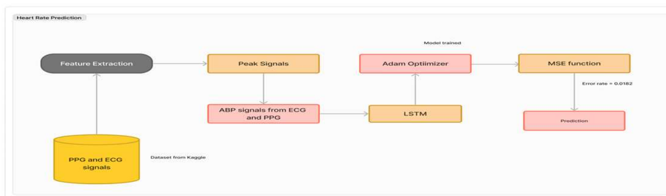

Fig. 3. Flow of Blood Pressure Prediction

Equations (1) (2) and (3) represent the general estimation of physiological parameters like BP and HR.Equations (1) and (2) represent the estimation of blood pressure based on remote photoplethysmography (rPPG) signals extracted from facial videos. Equation 3 describes the calculation of heart rate from the rPPG signals.

$$BP_{systolic} = f(rPPG_{signal}) \quad (1)$$

$$BP_{diastolic} = g(rPPG_{signal}) \quad (2)$$

$$HR = f(rPPG_{signal}) \quad (3)$$

Equations 4, 5 6 and 7 demonstrates the technical aspect of our study and represent the fundamental understanding for the estimation of BP and HR based on remote photoplethymsography (rPPG) signals extracted from facial videos. Equation 4 calculates the heart rate (HR) using the signal sampling frequency (fs) and the number of samples (N). This equation provides a fundamental understanding of how heart rate is estimated from the acquired signal. On the other hand, to estimate BP 5, employs the pulse transit time (PTT) to estimate blood pressure (BP). Here, k and b are constants determined through regression analysis. Additionally, the signal-to-noise ratio equation evaluates the quality of the signal relative to noise 6 , while the mean absolute error 7 quantifies the accuracy of our estimations by comparing actual and predicted values.

$$HR = \frac{f_s}{2N} \quad (4)$$

$$BP = k \times PTT + b \quad (5)$$

$$SNR = 10 \cdot \log10(\text{signal power}/\text{noise power}) \quad (6)$$

$$MAE = 1/n\ n\sum_{i=1 \text{ to } n}|yi - y\hat{}i| \quad (7)$$

We are utilizing the Non-Invasive Physiological Parameter Estimation dataset, which contains a diverse array of physiological signals acquired from various sensors. This dataset provides a diverse range of facial features and physiological signals for training and testing our model. The combination of this framework, mathematical formulations, and dataset forms the basis of our research, enabling the development of a non-invasive and accurate method for monitoring physiological parameters using laptop cameras.

IV. Discussion

Diseases intertwined with daily living have emerged as a significant societal challenge. Effective early identification and preventive interventions necessitate innovative, cost-effective, and non-invasive techniques. In addition to reducing the load on contact-based techniques, the COVID-19 era's lessons emphasize the necessity of non-invasive physiological monitoring. A notable rise in psychological problems occurred during this time, underscoring the necessity of contactless surveillance techniques to reduce the danger of secondary infections. Accepting non-invasive methods improves patient comfort and creates a proactive, adaptable healthcare framework that caters to the changing demands of contemporary society. Real-time tracking and management of health issues is facilitated by these technologies, which provide continuous monitoring without the discomfort and annoyance associated with traditional contact-based techniques.

Through our research, we have successfully shown that laptop cameras can predict blood pressure (BP) and heart rate (HR) within an acceptable error rate. This shows how computer vision and machine learning can revolutionize routine health monitoring into a seamless, inconspicuous process. This change emphasizes preventive care and individualized treatment plans, which not only supports a more holistic approach to health and wellness but also helps with early identification and intervention. Additionally, in order to increase the range of non-invasive monitoring, we plan to expand our methodology to evaluate additional physiological and psychological indicators like oxygen saturation, stress levels, and respiration rate.

Table 2.0 provides an overview of the studies, their methodologies, sample sizes, and limitations or future directions.

V. CONCLUSION

The exploration of non-invasive technologies for physiological and psychological parameter monitoring has indeed made significant strides, with innovative approaches contributing to an expanding landscape. Studies focusing on respiratory rate, mental stress, heart rate, mental stress and blood pressure highlight the versatility of these technologies. The utilization of laptop cameras for detecting daily lifestyle diseases shows promising results and has the potential to revolutionize healthcare.

The early detection of diseases through non-invasive monitoring can facilitate timely interventions, fostering preventive healthcare practices. Signal processing techniques such as Fast Fourier Transform, Principal Component Analysis, LSTM and machine learning algorithms have played a very important role in refining and optimizing these methodologies.

In conclusion, the dynamic field of non-invasive physiological parameter monitoring using laptop cameras has the potential to contribute substantially to healthcare improvements, emphasizing the need for ongoing research and development efforts to overcome existing challenges and ensure the widespread applicability of these technologies.

TABLE II: OVERVIEW OF STUDIES, THEIR METHODOLOGIES AND LIMITATIONS

S. NO	**Public-ations**	**Technology and sample size**	**Results (accuracy)**	**Disadvantage/ Limitations**
1.	[2]	Photoplethymsography signals with ViolaJones detection method for face detection and Kanade Lucas-Tomasi for feature extraction. (sample size:25)	94.6 %	Needs to be tested against more number of subjects, with natural real life movements.
2.	[3]	RGB camera to record PPG signals. Using correlation between PTT(Pulse transit time) and BP then regression model was used. (sample size: 5)	Highly correlated PTT and BP with mean error 0.18+/-5.50 mmHg (systolic BP) and 0.01 +/7.71 mmHg (diastolic BP).	Limited subjects, limited references to validate, low resolution camera.
3.	[4]	Photoplethymsography signal with KLT face detection algorithm and PCA, two tailed test. (sample size: 45)	For systolic and diastolic BP NMSE: 4.63% and 6.77%. MAE 3.90% and 3.72%. ESD 5.37% and 5.03% respectively.	Skin tone ignored and subjects were young and healthy.
4.	[5]	PPG signals with neural networks. (sample size: 20)	85% accuracy. And for systolic and diastolic BP average error rate 9.62% and 11.63% (for afternoon) and 8.4% and 11.18% (for evening) respectively.	Rest state subject, signals were affected by ambient light

5.	[10]	Smartphones with TOI (Transdermal Optical Imaging) and multilayer perceptron with 200 iterations. (sample size: 1328)	94.81% for systolic and 95.71% for diastolic BP	Only normotensive subjects were included: hypotensive and hypertensive subjects required. Needs to test in real life conditions for different skin tones. Continuous BP monitored: needs further model training and cross validation using gold standard techniques.
6	[6], [7]	PPG signals and ICA (Independent component analysis). (sample size: 12)	RMSE for HR (1.24), RR (1.28), HRV (0.92 for LH and RH)	Webcam fluctuations can vary based on the used PC, slower video sampling rate, less sample subjects, more validation required with subjects.
7.	[11]	Balistocardiography and image processing using Fast Fourier Transform.	-	Needs trials for proposed methodology.
8.	[13]	Photoplethymsography and Ballistocardiography and Fast Fourier Transform.	For Involuntary and voluntary head movements Mean Absolute error was .23 BPM (Beats Per Minute) and 2.78 BPM respectively	Focuses only on fixed light conditions, fixed camera position, and removes voluntary head movements out of scenario and only for laptop and tablet. Does not focus on hand motion and camera motion.
9.	[14]	Depth camera for Respiratory Rate monitoring, respiratory signals were monitored from patient's torso. (sample size: 7)	RMSD accuracy of 0.69 breaths/min with a corresponding bias of -0.034	Needs validation against more subjects, severe motions, patient and care taker interactions.
10	[15], [16]	rPPG with PCA to detect RR and mental stress. (sample size: 7)	MAD and RMSE of 0.714 BPM, 2.035 BPM respectively.	Processing time: Needs to be evaluated against processing time
11	[18]	Proposed algorithm with minimum hardware and facial data extraction	Average error of 2 BPM for heart rate, 4.6 BPM for respiration rate and 5% for blood oxygen saturation.	-
12	[19]	Mental stress detection via webcam. (sample size: 20)	80.31 % accuracy in different stress environments.	-
13	[34]	Six ML models: KNN, SVM, DT, LR, FR, MLP using bio signals ECG, EMG, GSR, and respiration rate, integrated with a Driver Assistance System (DAS). (drivedb dataset)	98.2 % accuracy by RF	Limited dataset and needs more validation for real life applicability.

FUTURE WORK AND LIMITATIONS

The successful monitoring of blood pressure (BP) and heart rate (HR) with a reasonable error rate is reviewed in this section, along with the theoretical framework for monitoring additional physiological and psychological parameters. Although there has been advancement in accuracy, further testing with larger numbers of samples is required to validate the reliability in real-world applications. Further research chapters will focus on combining these techniques to improve accuracy without affecting the convenience and affordability. This entails enhancing the user interface and optimizing the algorithms to make the technology more approachable and intuitive, so facilitating broad implementation in diverse healthcare contexts.

CONTRIBUTION

Three authors contributed equally to the writing, data analysis, technology, and theory of this study. The collaboration has produced comprehensive and comprehensive research results that demonstrate a shared commitment to the highest standards of scientific research.

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