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Evaluation of Classifiers for Non-Invasive Heart Rate Measurement Using Video Magnification

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ABSTRACT

As the current world approaches a better lifestyle, medical problems have also increased and gained a lot of attention in the last couple of years. Among others, heart rate detection has become a vital part of remote healthcare monitoring and diagnostic systems. The contactless heart rate measurement is a recent concept that monitors the colour changes in the skin, specifically the facial region, to assess the heart rate of the human. In this paper, the authors have presented an analysis of various machine learning classifiers and independent component analysis methods to support this concept, as the naked eye visualisation cannot detect minor changes in the face. Hence, machine learning and magnification of the frame become a vital step. The paper describes the general procedure of detecting the heart rate by monitoring the forehead of a live object. The training and classification procedure is discussed in detail, and a comparative analysis based on quantitative parameters for different machine learning classifiers is also presented in this paper. The analysis among various classifiers shows that the neural network with the highest accuracy proved to be a better machine learning classifier for heart rate detection work.

Keywords: Artificial intelligence, data mining, heart rate detection, machine learning, magnification

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INTRODUCTION

The contemporary society is currently striving towards enhancing the field of Human-to-computer (H2C) interaction to attain maximum benefits from machines. However, recent decades have also witnessed major health issues, such as cancer, heart failure, and brain disorders, due to technological advancements. Rochester medical research suggests that heart-related problems have increased due to several

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factors, including economic and mental stress (Krajnak, 2014) and food intake behaviour. Individuals in the workforce and office settings are particularly vulnerable to heart attacks due to excessive workloads, long shifts, and mental pressure that increase blood pressure (Alishahi et al.,2022). This research aims to establish a relationship between changes in facial appearance and heart rate due to stress. Modern life has resulted in individuals competing with millions of others, leading to anxiety, depression and other psychological and physical health issues. Unhealthy lifestyle choices, such as stress and poor diet, can lead to metabolic disorders, diabetes, joint problems, cardiovascular diseases, tumours, hypertension and obesity (Virtanen et al., 2012). Although technology has made life easier, it has drawbacks as well. Globally, heart-related deaths are increasing, accounting for 32 per cent of all deaths in 2019.

The World Health Organisation (2025) says that bad food, not getting enough exercise, smoking, and drinking too much alcohol are the main behaviours that put people at risk for heart problems (WHO,2025). Therefore, it is necessary to research cardiac problems and use technology to transform available data into valuable knowledge to facilitate better assessments of patients' health. This paper aims to monitor patients suffering from heart diseases, as changes in blood pressure can be fatal (Hwang & Lee, 2026). Facial colour changes are the first visible symptom, with the face turning red as blood pressure increases. At early stages, these changes are not easily identifiable, making it crucial to observe changes through magnified video. In such cases, the video is extracted into frames, and the forehead is selected as the Region of Interest (RoI). Male facial hair may interfere with the colour change detection, making the forehead the preferred RoI. Data mining refers to mining desired information. A data mining architecture is divided into three blocks, namely the input block, the processing engine, also referred to as the inference engine and the output block. The inference engine processes the supplied input values based on a stored repository that is supplied to the engine before putting it to any test. The general work diagram of data mining architecture is provided in Figure 1.

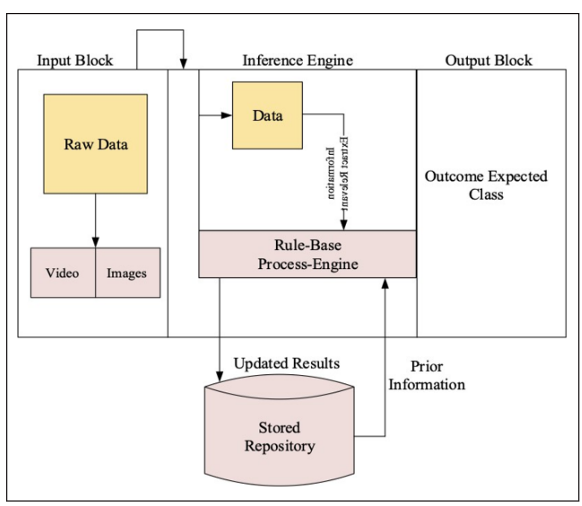

Figure 1. The general data mining architecture

Figure 1 shows the general data mining architecture for heart rate estimation, which highlights the stages involved in data acquisition, preprocessing, feature extraction, and classification. A data mining architecture is divided into three blocks, namely the input block, the processing engine, also referred to as the inference engine and the output block. The main components of a data mining architecture system are as follows:

Input Set	:	The input set contains the objects and their descriptions. The input might be a video, frames of a video, audio segments, images, etc. When it comes to medical data analysis, surveillance through videos has gained a lot of popularity (Ben et al.,2020). The visual aspects (Špetlík et al., 2018) provide a significant amount of information that becomes useful when it comes to training the system (Diller et al.,2014).
Inference Engine	:	The inference engine is the main working block of any data mining architecture, in which the inference engine processes the input values and decides based on the previous information stored in the repository. A stored repository is created using a training algorithm.
Output Set	:	The output set gives the final decision produced by the inference engine. As per prior knowledge stored in the repository and after applying basic rules and algorithms, the system generates outcome-based expected classes, which are utilised for classification and detection of the provided input data. This output is then utilised for analysis, validation or decision-making.

This study represents a structured comparative analysis of machine learning classifiers for non-invasive heart rate estimation within an ICA and video magnification-based framework.

The rest of the paper is organised in the following manner. Section 2 represents the search methodology employed in conducting the detailed literature review presented in Section 3, focusing on contactless heart measurement. Section 4 discusses the concept of training and classification algorithms and statistical machine learning metrics. The comparative analysis of the classifiers was conducted in Section 5 based on reported results from existing studies. The paper is finally concluded in Section 6.

The rigorous evaluation of lightweight machine learning classifiers in conjunction with an ICA-based signal extraction and video magnification framework for non-invasive heart rate measurement is the primary originality of this work. Unlike previous studies that primarily focus on deep learning-based approaches (Ben Ghezala, H. (2020) requiring large-scale datasets and high computational resources, this work focuses on computationally efficient models ideal for real-time and resource-constrained scenarios. Additionally, by providing a comprehensive comparison analysis within a single experimental flow, the paper exposes the trade-offs between computational complexity and accuracy. This makes the proposed method particularly relevant to edge-based healthcare monitoring systems.

METHODOLOGY

The review analysed the existing literature on the topic "heart rate detection using video samples", and the focus was given to the articles based on machine learning and independent component analysis. The academic databases referred to for the literature search include IEEE Explorer, Scopus, Google Scholar, etc in addition to Google search to ensure comprehensive coverage of the most relevant literature. The search statistics have involved articles published against two keywords, namely, "Heart Rate", "video samples", "machine learning", "independent component analysis", etc.

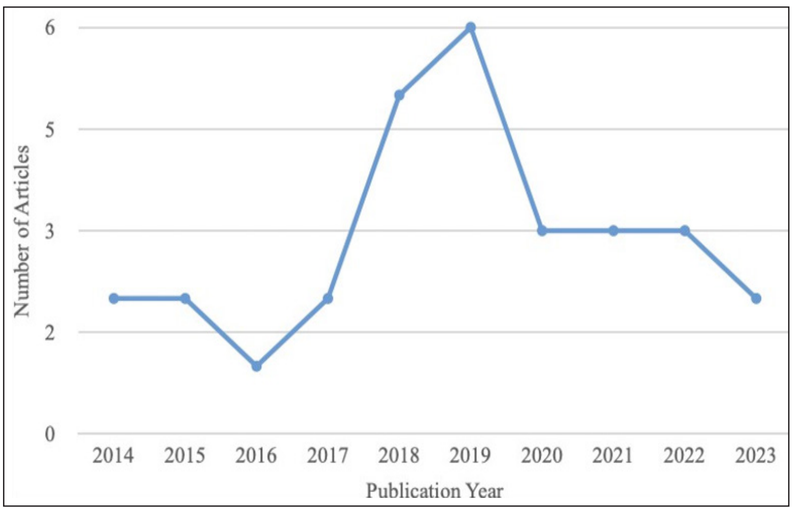

Figure 2. Distribution of articles used in the study

Figure 2 represents the number of articles considered in this study. In addition to several inclusion and exclusion criteria, the whole survey comprises papers published from 2014 to the present, and the number of papers covered from each year is graphically depicted in Figure 2. The screening process used here involves titles, abstracts, and full-text availability in addition to being a recent-year publication.

LITERATURE REVIEW

Contactless techniques to measure heart rate have gained more attention in recent years due to their non-invasive and remote features (McDuff et al.,2015). It has gained high popularity in the healthcare industry to monitor fitness and handle healthcare concerns using human-computer interaction. To measure heart rate, thermal imaging, facial videos, and photoplethysmography (Acharya et al., 2025), signals play a very important role. In a study by Xiaochuan et al. (2016), a digital camera was used to capture conventional wrist movies, and the Eulerian video magnification (EVM) method was used to detect the wrist pulse signals non-intrusively. The signals were analysed using the 2-Gaussian curve modelling approach, and the frames of the captured films were subjected to spatial decomposition and temporal filtering. The results of the experiments showed that the EVM approach may be used to capture the properties of the wrist pulse signal and can be utilised to anticipate major cardiovascular events. Rizvi et al. 2018 modified the EVM video post-processing control settings using the PCB-IDE and used the differential algorithm using selective mutation (DE/rand/1/bin) to provide an EVM control parameter tuning method. The suggested PCB-IDE aids specialists in choosing the best settings for the EVM process, and the interactive parameter estimation through PCB-IDE is viable, although it suffers from user fatigue limitations. Next research should focus on developing application-specific meta-models to alleviate user fatigue and further the optimisation process's exploration of the population space. There are several researchers who have taken advantage of Independent Component Analysis as a powerful signal processing technique to analyse mixed and complex signals generated due to skin colour, physiological signals and motion artefacts (Casalino et al.,2019).

An innovative technique for remote photoplethysmography signal measurement from facial movies is presented by Yu, Li, et al. 2019. Their method, which makes use of Spatio-Temporal Networks, shows encouraging results in non-invasive physiological monitoring. The work could benefit from addressing potential issues with lighting and subject diversity; however, it lacks thorough validation on a variety of datasets. Overall, this study is an important step towards convenient and accessible health monitoring, but more study is required to increase its robustness and generalizability.

The use of highly compressed facial recordings (Peng et al., 2019) offers an amazing deep learning method for remote heart rate assessment (Debnath et al.,2025). Their approach has great potential for non-invasive health monitoring. The method is impressively able to extract heart rate data in challenging video conditions. However, it's vital to keep in mind that extra testing and validation on a larger dataset are valuable in establishing the practical utility and generalizability of the proposed system. Overall, the field of computer vision for healthcare applications has advanced significantly because of this study.

In the area of remote photoplethysmography, Hu et al. (2019) demonstrated a cutting-edge strategy. They demonstrated the potential of their technique for non-invasive health monitoring applications by showcasing notable developments in the spatial-temporal information capture field. The study, however, was hampered by a lack of readily available data, which might have affected how broadly applicable their findings were. Despite this, the novel convolutional neural network design by the scientists and its encouraging results represent a substantial advancement in the field of remote PPG research.

Zarezadeh and Rezaeian (2016) offered a novel method for recognising face micro-expressions using the EVM approach to extract the fine movements of the face. The eigenface methodology was applied to detect micro-expressions in the SMIC database and classify detected micro-expressions as negative vs positive in the SMIC database and pleasure versus disgust in the CASME database. The findings demonstrated that using the eigenface approach with the EVM method to retrieve minor facial movements improves micro-expression identification performance. Yu, Peng, et al. (2019) demonstrated how video sequences may be used to get dynamic heart rate readings, which are generally collected from sensors placed near the heart. An independent component analysis (ICA) combined with mutual information was used to make sure that accuracy is not lost while using short video durations. Experimental findings demonstrated that the suggested approach may be utilised to quantify dynamic heart rates, with RMSE and correlation coefficients of 1.88 BPM and 0.99, respectively. A system proposed by Antink et al. (2019) multimodal sensor fusion approach for discrete vital sign monitoring. The technique used skin colour fluctuations and the head motion signal taken from a webcam video. Their findings prove that the proposed technique is effective for unobtrusive and continuous monitoring of both heart rate and respiration rate. A Multi-hierarchical Convolutional Network (MCN) was developed by Zhang et al. (2021) for effective remote photoplethysmograph (rPPG) signal and heart rate prediction from facial video. The main objective of the study was to improve the accuracy and computational efficiency of rPPG-based heart rate estimation. MCN extracted the spatial and temporal features from facial video data by using hierarchical convolutional layers to predict reliable heart rates from video recordings. The study generates promising results. However, variations in illumination and facial expressions make the model susceptible to noise, and it may affect the quality of rPPG signals and, consequently, heart rate measurement.

Hu et al. (2021) proposed ETA-rPPGNet, an Effective Time-Domain Attention Network to enhance accuracy and robustness for remote heart rate measurement from facial images. The network employs time-domain attention procedures that focus on relevant temporal features, which help improve heart rate estimation accuracy. The study proved a considerable improvement in heart rate estimation accuracy when it is compared to existing techniques. The increase in computational complexity of the attention mechanism may affect its feasibility for real-time processing on resource-constrained systems.

Cotes et al. (2022) proposed an observational research study on assessing schizophrenia and depression using multiple modalities, incorporating heart rate technologies. The objective of the work was to explore whether multimodal data, including heart rate, can support diagnosis and evaluate mental conditions. The report presents findings that highlight important information about how to integrate heart rate information into mental health assessments. The complexity of analysing and processing multimodal data is a significant challenge, and it requires data fusion and analysis methodologies.

Hu et al. (2022) introduced a Spatial-Temporal Attention Network to provide a robust heart rate estimate from face images. The research focused on enhancing the accuracy of heart rate measurement under challenging conditions like facial movements and noise. The network utilises spatial-temporal attention procedures to focus on essential regions and frames in the video frame. The study demonstrated notable improvements in heart rate estimation and accuracy, however, in difficult situations. A major problem could be the requirement for a large amount of training data to generalise well across varied individuals and conditions.

A technique to estimate heart rate and heart rate variability in real-time from photographs is put forth by Su et al. (2023). The authors aimed to make picture data available for real-time vital sign monitoring. Heart-related signals from image sequences are extracted using an approach that combines independent component analysis and particle swarm optimisation. The creation of an unobtrusive, real-time heart rate monitoring device is one possible result of this research. The accuracy of heart rate variability estimation, however, could be problematic because it can be impacted by several things, such as motion (Estepp et al.,2014), artefacts and picture data noise.

ViT-rPPG, a network based on vision transformers for remote heart rate measurement, is presented by Sun et al. (2023) with the sole aim of using vision transformers to boost the precision of remote heart rate estimation. The study shows how well ViT-rPPG captures temporal characteristics from video data, yielding precise heart rate estimations. The computational demands of vision transformer networks, however, provide a major obstacle and may prevent their use on devices with limited resources.

A detailed comparative analysis of recent studies aimed at heart rate measurement based on face videos is summarised. Independent component analysis has played a very important role in improving the capabilities of machine learning-based mechanisms involved in contactless heart rate measurements.

Table 1 shows that a few public datasets have been widely used in the simulation analysis by several researchers in recent years. Further, the observed accuracy by which the HR has been measured and the correlation coefficient are also common evaluation parameters that helped the research community to evaluate their work.

The development of non-invasive techniques for monitoring cardiovascular health depends heavily on video files for heart rate measurement investigations. These datasets are used to create and test algorithms that can predict heart rates without having direct contact with a person's skin or pulse. Typically, these datasets are video recordings of people's faces or bodies. As an outcome of the detailed analysis of the review, several video datasets came to light, including PURE, OBF, MAHNOB-HCL, etc., that have demonstrated several applications in addition to some of the self-recorded sample datasets. In addition to this, there also exist a large number of datasets with a variable number of subjects and videos to support training and evaluation of machine learning models and Popular datasets such as DEAP (Koelstra et al., 2012), MAHNOB-HCI (Soleymani et al., 2012), and UBFC-rPPG (Bobbia et al., 2017) are widely used for rPPG evaluation. A handful of them are summarised in Table 2 to provide a broad option to the reader for the selection of the dataset for future research.

Table 1
Summary of heart rate measurement techniques

Year	Citation	Objective	Technique	Dataset	Parameter
2017	Singh et al., 2017	Contactless real-time heart rate measurement	Kalman-Lucas-Tomasi (KTL) Face De- tection Algorithm, Independent Component Analysis (ICA), Fast Fourier Transform (FFT)	Self-Recorded Dataset	Heart Rate Measurement and Accu- racy
2017	Alghoul et al., 2016	Heart rate traction variability ex-	Independent Component Analysis (ICA) and Empirical Mode Decomposition (EMD)	Not Specified	Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Correlation Coefficient
2018	Špetlík et al., 2018	Visual Heart Rate Estima- tion with CNN	Convolutional Neural Network	204 fitness-themed videos of 20 to 53-year-old subjects	HR accuracy (MAE) Mean Absolute Error
2018	Chen & McDuff, 2018	Video-based physiological measurements (HR, blood volume pulse, breathing rate)	Convolutional Attention Networks	3 datasets of RGB videos and 1 dataset of IR videos	Measurement accuracy, Signal to Noise Ratio, Correlation Coefficient
2018	Casalino et al.,2019	Monitoring cardiovascular risk in real-time without contact	Independent Component Analysis (ICA), Fast Fourier Transform (FFT)	Self-Recorded Dataset of 116 patients	Heart Rate, Breath Rate, Accuracy, Positive Predictive Value, True Positive Rate
2019	Yu, Li, et al., 2019	HR measurement from facial videos	Spatio-Temporal Networks	OBF and MAHNOB-HCI	Accuracy, Pearson Correlation Coefficient
2019	Yu, Peng, et al., 2019	HR measurement from com- pressed facial videos	Deep learning and video enhancement	2 video datasets	Accuracy, Pearson Correlation Coefficient
2019	Hu et al., 2019	Remote HR measurement	Spatio-Temporal Convolutional Neural Networks	PURE and COHFACE datasets	Accuracy, Pearson Correlation Coefficient

Table 1 *(continued)*

Year	Citation	Objective	Technique	Dataset	Parameter
2019	Qiu et al., 2022	Heart rate measurement from face videos	Independent (ICA) Component Analysis	112 videos recorded with 201600 frames	Mean absolute deviation (MAD), root mean square error (RMSE) and the Pearson correlation coefficient
2020	Yu et al., 2020	HR measurement with neural searching	End-to-end neural searching	VIPL-HR datasets and MAHNOB-HCI	Accuracy, Pearson Correlation Coefficient
2021	Hu et al., 2021	Remote HR measurement	Time-domain Attention Network	UBFC rPPG Dataset, COHFACE Dataset, Pulse Rate Detection Dataset, and MMSE-HR dataset	Accuracy, Pearson Correlation Coefficient
2022	Hu et al., 2022	HR measurement from facial videos	Spatio-Temporal Networks	Pulse Rate Detection Dataset and COHFACE dataset	Accuracy, Pearson Correlation Coefficient
2022	Cotes et al., 2022	Multimodal Assessment using EEG, HR technology, etc	Machine Learning Model	Self-Recorded Dataset	Pearson Correlation Coefficient
2023	Su et al., 2023	Measure Heart Rate Variability	Independent Component Analysis (ICA) and Particle Swarm Optimisation (PSO)	Self-Recorded Data from 20 subjects	RMSE and mean absolute error percentage (MAPE), Correlation Coefficient
2023	Sun et al., 2023	Remote HR measurement	Deep learning Model for a vision transformer-based network	Mixed dataset	Computational Complexity and Signal Fitting
2023	Li et al., 2023	HR measurement from video clips	Multi-hierarchical Convolutional Network	UBFC-RPPG and COHFACE datasets	Accuracy, SNR, MAE

Table 2
Datasets for heart rate measurement

Name of the Dataset	Number of Subjects	Number of Videos	Description
PURE (Stricker et al., 2014)	10	60	Recorded for different activities
OBF (Li et al., 2018)	106	2120	Facial videos recorded in reference to physiological signals
MAHNOB-HCI (Soleymani et al., 2012)	27	527	Short videos with human actions
DEAP (Koelstra et al., 2012)	32	120	Frontal face recordings of human affective states
MMSE-HR (Qiu et al.,2022)	40	102	Captured under various facial expressions
VIPL-HR (Niu et al., 2019)	107	3130	Collected using smartphones to support remote heart rate estimation
UBFC-RPPG (Bobbia et al., 2017)	Typically small	10-20	Collected conditions under variable
EmotiW (Dhall et al., 2020)	30-50	Variable	Videos of different facial expressions for heart rate estimation

Further, the included papers showcase the promising possibility for non-invasive and real-time monitoring and demonstrate the ongoing developments in contactless vital signs measurement, particularly in remote heart rate estimation. Recent studies have explored deep learning-based approaches such as CNN and rPPG, while these methods give high accuracy but require a large dataset. For further study in this area, difficulties, including computational complexity and susceptibility to external influences, must still be considered. Datasets should be based on their specific goals and requirements.

Techniques and Methods

The review reflected that ICA is not a mainstream method chosen for heart rate or variability measurement. It offers versatility and shows its greater implications when dealing with some specific contexts, such as multi-sourced data. As such, it is majorly integrated with machine learning techniques for validation to assure utilizing critical aspects of independent component analysis in the context of heart rate measurement (Gao et al., 2024). The most popular ICA methods used in this context are spatial, temporal, frequency domain, multichannel and physiological priors. A comparison among these is given in Table 3 to have a clear idea of possible limitations and suitability before their implication.

The method chosen is determined by the specific application and constraints. The first approach may be adequate for scenarios with low motion; the second or third methods may be more appropriate for more complex scenarios, particularly those with motion. In the end, the accuracy of the heart rate measurement will be determined by parameters such as data quality, camera resolution, and illumination conditions, in addition to the ICA method used.

Table 3
Popular ICA methods

ICA Method	Scalability	Suitable Sample Size	Accuracy	Advantages	Limitations
Spatial ICA	Yes	Large	Good to Excellent	Proficient in handling spatial variations	A very careful filter selection is required
Temporal ICA	Yes	Medium	Moderate to Good	Simple and computationally efficient	Highly vulnerable to motion artefacts
Frequency Domain ICA	Yes	Medium	Good to Excellent	Effective in frequency domain	Sensitive to artifacts and noise
Multi-channel ICA	Yes	Large	Excellent	Efficient in utilising data from multiple cameras	Calibration and synchronisation is required among cameras
ICA with Physiological Priors	Yes	Large	Excellent	Uses preexisting knowledge of physiological signals	May not be adapt the variations

Training and Testing Mechanisms

Independent component analysis is one of the most popular statistical signal processing techniques that has been associated with most of the popular heart rate measurement methods, such as photoplethysmography and electrocardiography, to analyse physiological sensor data.

This involves temporal dynamics of the extracted features of heart rate-related components; however, it faces many challenges with complex and noisy data. Hence, combined with machine learning techniques. The training and classification are done based on the training engine and classification engine. Artificial Intelligence is a very fascinating concept that is strongly associated with the concepts of data mining and rule mining. Machine Learning, A branch of AI, is divided into two stages: training and testing. The first phase suggests a learning process based on several well-known dataset properties. Phase two uses the knowledge picked up in the first to develop predictions about unidentified features. "Training and testing" are also referred to as "learning and prediction" from this perspective. The goal of ML is to develop a model that can be used to predict future events using a learning algorithm. As a result, this practice is known as forecasting. These terms are widely used in present-day research to improve the standards of work as well as an individual's day-to-day life. In rule mining, the learning concept of various machine learning algorithms mentioned in Table 4 is used to analyse the correlation among the frequently occurring patterns or the categorical data from the databases or repositories.

Table 4
Comparative analysis of popular machine learning techniques

Technique	Category	Type	Areas of Application	Advantages	Limitations
Linear Regression	Supervised	Regression	Predicting numeric values	Simple, efficient for linear data	Limited to linear relationships
Logistic Regression	Supervised	Classification	Binary classification	Simple and provides probability estimates	Limited to classification binary
Decision Trees	Supervised	Classification /Regression	Classification, Regression	Can handle non-linear relationships	Prone to overfitting, unstable for small changes
Random Forest	Supervised	Ensemble	Classification, Regression	Reduces over-fitting, handles complex relationships	Less interpretable, slower training
Support Vector Machines (SVM)	Supervised	Classification /Regression	Classification, Regression	Effective For high- dimensional data, versatile kernel functions	Very sensitive to hyperparameters, slow training
K-Nearest Neighbours (KNN)	Supervised /Un-supervised	Classification, Regression, Clustering	Classification, Regression, Clustering	Simple, no training required, works well with small datasets	Computationally expensive for large datasets
Naive Bayes	Supervised	Classification	Text classification, spam detection	Fast and works well With high-dimensional data	Assumes independent features, not suitable for complex relationships
Neural Networks	Supervised	Deep Learning	Image recognition, NLP, complex tasks	Versatile and can learn complex patterns.	Complex architecture, require large datasets
K-Means Clustering	Unsupervised	Clustering	Data segmentation, customer segmentation	Simple and efficient with large datasets	Very sensitive to initial cluster centroids
Principal Component Analysis (PCA)	Unsupervised	Dimensionality Reduction	Feature selection, noise reduction	Reduces dimensionality, retains most variance	Assumes linear relationships, loss of interpretability

To assess heart rate using video data, machine learning approaches have become increasingly popular. They solve several major problems in this field. The following are some of the principal difficulties that machine learning methods can aid in overcoming:

- **Skin tone and lighting conditions:** A person's skin colour and brightness can be influenced by a variety of factors, including skin tone, ambient lighting, and camera quality. By normalising for skin tone and correcting for lighting conditions, machine learning algorithms may be trained to adapt to these differences and retrieve reliable heart rate information.
- **Face Tracking:** To detect heart rate accurately, continuous detection of the face and tracking are required. Machine learning algorithms can accurately detect and track even when the person is moving or only partially visible.
- **Calibration:** To improve the precision of heart rate measurement, machine learning models can be adjusted and fine-tuned. This process may entail collecting ground truth data to adjust and validate the system.
- **Interference and Noise:** Videos may contain multiple sources of noise and interference, such as background movements, music, illumination changes or any surrounding environmental conditions. Machine learning models can be trained to exclude irrelevant signals and keep meaningful components, which are required for heart rate extraction.
- **Motion Artefacts:** Motion artefacts occur when the camera or the person moves during recording, which can distort facial features used to estimate heart rate. Machine learning models are trained to remove these artefacts, which helps to increase the overall accuracy of heart rate readings.

Hence, by using machine learning algorithms, several problems can be resolved with heart rate measurement from video data. One of the biggest issues is the need for exact and non-invasive measurements. Machine learning algorithms can determine heart rate by detecting minute differences in blood flow, motion, and facial colour without the use of intrusive instruments. Another issue is robustness to multiple circumstances, such as different skin tones, lighting, and facial expressions. Machine learning models can be trained on a variety of datasets to boost generalisation and account for these differences

Estimation Matrices

When it comes to machine learning, the computation of the error metrics is involved in the analysis. The predictions and the estimations performed using machine learning techniques are analysed using correlation metrics such as standard error, root mean square error, and standard deviation. Statistical Machine Learning (S-ML) refers to calculating the parametric values using stats viz. numeral values. Mean Squared Error (MSE) and

Standard Error (SE) are perfect examples of S-ML architecture. Sometimes additional validation is also performed using some similarity indices, for instance, cosine similarity, soft cosine, Jaccard, etc.

Standard Error (SE)

This statistical term is used to quantify the accuracy with the help of a sample distribution to represent a population using the standard deviation. It is used to refer to the standard deviation of different sample statistics, like the mean or median. To compute the value of standard error, Equation 1 is used.

$$SE = \sigma/\sqrt{n} \quad [1]$$

Where SE is defined as the standard error of the sample, n is defined as the number of samples, and σ defined as the sample standard deviation.

Root Mean Square Error (RMSE)

It is the standard deviation of the predicted errors found when estimating effort. The distance from the distribution to the regression line is calculated. Equation 2 is used to compare the experimental results to the project's estimated and desired output.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (E_{predicted} - E_{actual})^2} \quad [2]$$

Mean Squared Error (MSE)

It is the measure of the quality of the estimator used in the prediction analysis. It is mathematically represented as the mean value of the squared difference between the predicted and the observed values of the parameter under study. In this prediction, the lower the value, the better the predictions reflect the better quality of the estimator. To compute the MSE, Equation 3 is used.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Observed_{value} - Predicted_{value})^2 \quad [3]$$

Standard Deviation (SD)

The degree of dispersion seen in a set of values is indicated by this parameter. It indicates that the calculated values are near the predicted values when they are low. It is calculated using the following Equation 4.

$$SD = \sqrt{\frac{\sum E_{value} - Mean_{value}}{Proj_{total}}} \quad [4]$$

Where E_{value} is the computed value and $Mean_{value}$ is the mean of the computed values over the number of project files $Proj_{total}$. To compare the effectiveness of the classifiers, a quantitative parameter analysis is done.

Precision

It is the metric that is used to measure or assess the correctness of the designed methodology to reflect positive predictions made during testing. The formula for precision calculation is given in Equation 5.

$$Precision = True_{positive} / (True_{positive} + False_{positive}) \quad [5]$$

Recall

It's a metric that quantifies the completeness of positive predictions made during the testing phase. It is computed by dividing the number of true positives by the sum of true positives and false negatives. Equation 6 is mentioned below to find the Recall value.

$$Recall = True_{positive} / (True_{positive} + False_{negative}) \quad [6]$$

F-measure

It is the statistic that creates a single score by combining recall and precision. It is computed by taking the harmonic mean of precision and recall. Equation 7 represents the formula to compute F-measure.

$$F - measure = 2 * (Precision * Recall) / (Precision + Recall) \quad [7]$$

Accuracy

It is a number that assesses the test's overall accuracy. It is computed by dividing the total number of cases by the sum of true positives and true negatives, as mentioned in Equation 8.

$$(TP + TN) / (TP + FP + TN + FN) \quad [8]$$

These are the popular metrics used for assessing the effectiveness of the designed classification approaches for heart rate measurement. The outcomes are usually tested in reference to the ground truth and expressed in terms of these metrics.

RESULT AND DISCUSSIONS

Although deep learning methods such as CNNs and Transformers have demonstrated remarkable accuracy in rPPG-based heart rate estimation, they often require large, annotated datasets and significant processing resources. In contrast, this study focuses on evaluating lightweight machine learning models that are more suitable for real-time deployment on edge devices with limited processing capability. This trade-off between processing performance and accuracy is critical for practical healthcare applications.

There are numerous algorithms in the large field of machine learning, each of which is created to tackle a particular class of issues. The effectiveness and performance of a machine learning model can be significantly impacted by the algorithm of choice. Therefore, it is crucial to conduct a comparative analysis before selecting an algorithm.

To evaluate the effectiveness of various machine learning techniques, the analysis is based on precision, recall and F-measure based on the training and classification data. The distribution is 70-30, where 70% of the data is applied for training, and the remaining 30% of the data is used for classification. In total, there are 2000 frames for the comparison with different classifiers. For the classification process, multiple machine learning algorithms have been applied, namely the Feedforward backpropagation algorithm as ANN, K-nearest neighbour (KNN), Naïve Bayes and Multiclass Support Vector Machine (SVM). Table 5 illustrates the comparative analysis based on Precision, Recall and F-measure.

Table 5
Average precision and recall analysis

'Number of Samples'	'Precision ANN'	'Precision Naive Bayes'	'Precision KNN'	'Recall ANN'	'Recall Naive Bayes'	'Recall KNN'
500	0.96476531	0.95774648	0.96052632	0.98666667	0.90666667	0.97333333
700	0.96286655	0.95959596	0.95918367	0.98058252	0.9223301	0.91262136
1000	0.95630247	0.94308943	0.95488722	0.99230769	0.89922481	0.97692308
1200	0.96134457	0.95205479	0.95031056	0.98734177	0.87974684	0.98076923
1400	0.9626129	0.95811518	0.95744681	0.98924731	0.98387097	0.97297297
1600	0.96621961	0.95145631	0.95049505	0.99065421	0.92018779	0.90140845
1800	0.96763848	0.95652174	0.95951417	0.98760331	0.91286307	0.97933884
2000	0.95845314	0.95112782	0.95255474	0.99256506	0.94402985	0.97752809

The given parameters represent the performance metrics of three classification algorithms: Artificial Neural Network (ANN), Naive Bayes, and K-Nearest Neighbour (KNN) on a test set of 2000 samples. These metrics are Precision, Recall, F-measure, and Accuracy. In this response, these metrics are discussed and compared to the performance of the three algorithms.

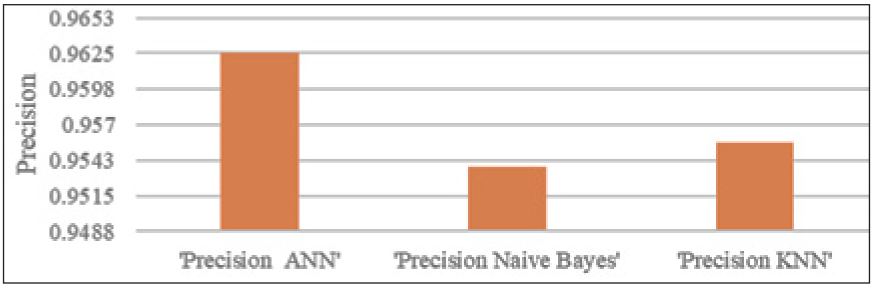

Figure 3. Average precision analysis

Figure 3 shows the comparative analysis of average precision attained by different classifiers.

Precision

Precision measures the fraction of true positives (properly detected instances) out of the total instances projected as positive. A higher precision value of an algorithm indicates that it is more accurate in identifying positive cases. The average precision of ANN is 0.9625, which is slightly higher than that of Naive Bayes (0.9537) and KNN (0.9556). This shows that ANN performs better than Naive Bayes and KNN in identifying positive instances.

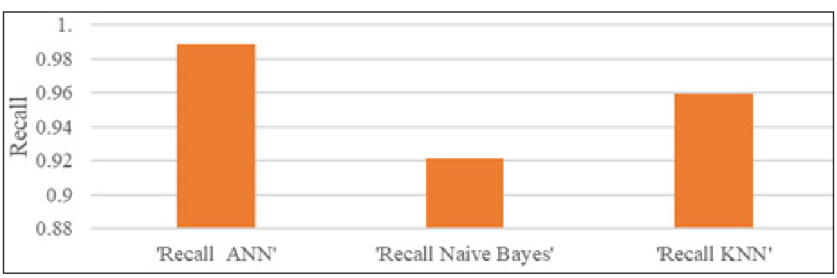

Figure 4. Average recall analysis

Figure 4 shows the average recall values for the classifiers, which indicate their ability to correctly identify positive instances.

Recall

Recall refers to the completeness of positive predictions made during the testing phase. A higher recall implies that the algorithm is more effective in detecting positive instances. The average recall of ANN is 0.9884, which is higher than that of Naive Bayes (0.9211) and KNN (0.9594). This demonstrates that ANN gives better efficiency than Naive Bayes and KNN in identifying positive instances.

F-measure

F-measure creates a single score metric by combining recall and precision, as shown in Table 6. The average F-measure of ANN is 0.9753, which is higher than Naive Bayes (0.9369) and KNN (0.9572). This indicates that ANN gives better output for balanced precision and recall than Naive Bayes and KNN.

Table 6
F-measure and accuracy

'Number of Samples'	'F-measure ANN'	'F-measure Naive Bayes'	'F-measure KNN'	'Accuracy ANN'	'Accuracy Naive Bayes'	'Accuracy KNN'
500	0.97559309	0.93150685	0.96688742	92.5	85	91.25
700	0.97164379	0.94059406	0.93532338	91.8181818	86.3636364	85.4545455
1000	0.97397244	0.92063492	0.96577947	92.1428571	82.8571429	90.7142857
1200	0.97416976	0.91447368	0.96529968	91.7647059	81.7647059	90
1400	0.97574839	0.97082228	0.96514745	92	91.5	90
1600	0.97828435	0.93556086	0.9253012	92.173913	85.2173913	83.4782609
1800	0.97751896	0.93418259	0.96932515	91.9230769	84.6153846	91.1538462
2000	0.97521089	0.94756554	0.96487985	92.0689655	87.2413793	90

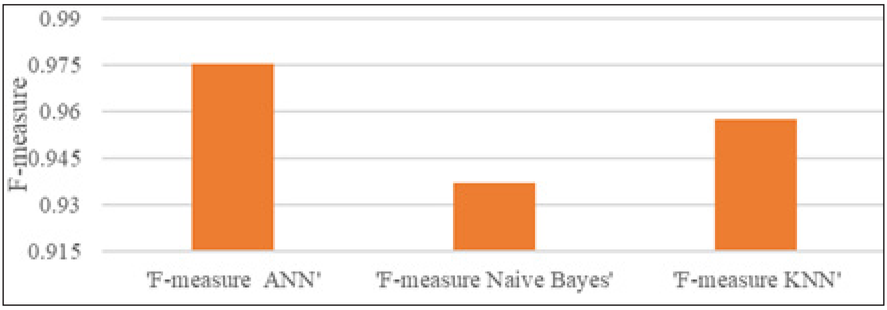

Figure 5. Average F-measure analysis

Figure 5 presents the average F-measure analysis, which indicates the balance between precision and recall.

Accuracy

Accuracy is a number that assesses the test's overall accuracy. It is one of the most used metrics for evaluating classification algorithms. The average accuracy of ANN is 92.049%, which is higher than Naive Bayes (85.570%) and KNN (89.006%). The high accuracy of ANN indicates it provides more accurate classification than Naive Bayes and KNN.

Figure 6 shows the overall performance comparison of the classifiers based on accuracy and other evaluation metrics.

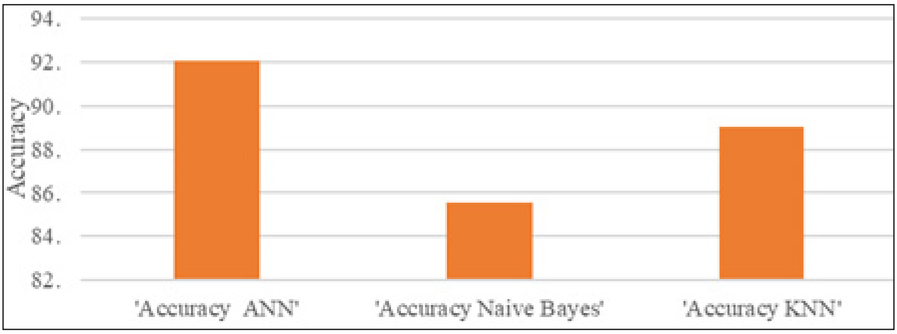

Figure 6. Average performance analysis

Overall, the performance metrics suggest that ANN performs better than Naive Bayes and KNN across precision, recall, F-measure, and accuracy. The percentage improvement of ANN over Naive Bayes and KNN can be evaluated as given below:

- Precision improvement over Naïve Bayes = (0.9625 - 0.9537) / 0.9537 * 100% = 0.92% and over KNN = (0.9625 - 0.95561) / 0.95561* 100% = 0.73%
- Recall improvement over Naïve Bayes = (0.9884 - 0.9211) / 0.9211 * 100% = 7.31% and over KNN is = (0.9884 - 0.95932) / 0.95932 * 100% = 3.02%
- F-measure improvement over Naïve Bayes = (0.9753 - 0.9369) / 0.9369 * 100% = 4.10% and over KNN is = (0.9753 - 0.95724) / 0.95724 * 100% = 1.88%
- Accuracy improvement over Naïve Bayes = (92.049 - 85.570) / 85.570 * 100% = 7.57% and over KNN is = (92.049 – 89.569) / 89.569 * 100% = 3.41%

The above-mentioned calculations indicate that ANN offers a slight improvement in precision, a substantial improvement in recall, a moderate improvement in F-measure, and a major improvement in accuracy as compared to both Naive Bayes and KNN.

In short, the performance metrics precision, recall, F-measure, and accuracy clearly indicate that the performance of ANN is better than Naive Bayes and KNN. However, the improvement varies across different metrics of ANN over Naive Bayes and KNN, but overall, the enhancement provided by ANN is important. These results suggest that ANN is a better choice for classification tasks than Naive Bayes and KNN, at least in the context of the given test set. The goal of this procedure is to identify the algorithm that best satisfies the requirements of the given problem by comparing numerous algorithms based on a variety of criteria. The importance of comparative analysis in machine learning, the essential processes in conducting one, and the effects it has on model performance and decision-making.

Ablation Analysis of Key Components

A conceptual ablation analysis is provided to highlight the importance of various heart rate estimation components based on findings stated in the literature.

The major factors include video magnification, machine learning model classification, Independent Component Analysis (ICA) signal extraction, and Region of Interest (ROI) selection. Previous research implies that the absence of ICA leads to reduced signal quality due to increased noise and interference. Also, the absence of video magnification reduces estimation accuracy, which makes it more difficult to recognise minute physiological indicators. Inappropriate ROI selection also introduces artefacts caused by movement, occlusion, or changes in light. Each component contributes significantly to the overall performance of the system. So, this analysis shows that the section of ROI video magnification feature extraction and selection plays a crucial role in enhancing heart rate estimation accuracy and robustness.

CONCLUSION

The paper presents an analytical study of the methods and techniques used for heart rate measurement. This paper reviews commonly used datasets and parameters that are mostly used for the assessment of heart rate measurement work. A comparative performance analysis is provided of different machine learning classifiers based on the quantitative parameter. This analysis indicates that ANN performs better than the other state-of-the-art classifiers. The average precision of ANN is 0.9625, which is slightly higher than Naive Bayes (0.9537) and KNN (0.9556). This suggests that ANN is more accurate in identifying positive instances than Naive Bayes and KNN. The average recall of ANN is 0.9884, which is also higher than Naive Bayes (0.9211) and KNN (0.9594). This shows that ANN is better at identifying positive instances than Naive Bayes and KNN. The average F-measure of ANN is 0.9753, which is higher than Naive Bayes (0.9369) and KNN (0.9572). From this result, it is understood that ANN provides a better balance between precision and recall than Naive Bayes and KNN. The average accuracy generated by ANN is also 92.049%, higher than that of Naive Bayes (85.570%) and KNN (89.006%). These results indicate that ANN provides the most consistent performance. However, these findings are based on the comparative analysis of existing studies, and results may vary depending on the dataset and experimental conditions.

Future research will focus on improving the reliability and real-world applicability of non-invasive heart rate estimation techniques. This involves integrating multimodal datasets that combine facial video with physiological and demographic parameters, as well as using advanced feature extraction techniques for enhanced resilience to motion and illumination variations (Liu et al., 2024), according to recent research (Buyung et al., 2024). To increase accuracy and generalisation, hybrid methods that combine deep learning models with conventional signal processing may also be investigated. Further validation using large public datasets and real-time deployment on mobile and edge devices will be considered to facilitate practical healthcare applications.

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LIST OF ABBREVIATIONS

ICA	:	Independent component analysis
EVM	:	Eulerian video magnification
HR	:	Heart rate
BP	:	Blood pressure
HRV	:	Heart rate variability
rPPG	:	Remote photoplethysmography
ROI	:	Region of Interest
RGB	:	Red green blue
CNN	:	Convolutional neural network
DNN	:	Deep neural network
PSO	:	Particle swarm optimisation
FA	:	Firefly algorithm
SIFT	:	Scale-Invariant feature transform
SURF	:	Speeded-Up robust features
MSER	:	Maximally stable extremal regions
PCA	:	Principal Component Analysis
RMSE	:	Root mean square error

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