International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 16 (2024) pp. 197–209

Article

Hospital Remote Care Assistance AI to Reduce Workload

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Received date: 5 April 2024; Accepted date: 26 May 2024; Published online: 24 May 2024

Abstract: In the ever-evolving healthcare landscape, the rapid advancement of Artificial Intelligence (AI) technology presents significant opportunities for enhancing patient care and streamlining operational workflows. This study adopts the action research methodology to explore the transformative impact of AI, specifically leveraging data fusion techniques, on remote chronic patient care. Our research yields promising results, achieving 94% accuracy in predicting heart rate abnormalities using Neural Networks and 87.6% for Facial Expression classification through Convolutional Neural Networks. A critical observation from the state-of-the-art indicates that existing studies predominantly focus on remote patient monitoring, leaving a substantial gap in addressing the needs of caregivers and medical staff. Our findings demonstrate that AI, integrated into remote home care monitoring systems, has the potential to alleviate caregiver workloads by enabling continuous patient monitoring and timely alerts. The automation of data extraction and analysis enhances healthcare professionals' decision-making capabilities, ultimately improving patient outcomes while alleviating the burdens of manual data entry.

Keywords: artificial intelligence; remote patient monitoring; workload; data mining; machine learning; data fusion

1. Introduction

Statistics show that in many European nations, the proportion of elderly individuals in the overall population is continuously rising, and it is anticipated that this trend will continue in the ensuing decades. This will result in a rise in the number of elderly persons who require care [1]. Therefore, the need for home care will increase, since many individuals pick home care above every other type of care, and in an urban setting, the number of persons able to care for dependent family members decreases when the typical large family group is broken up into small family units [2].

Home Care Systems (HCS) may offer clear advantages over conventional forms of care, since they do not require patients to visit a doctor's office, clinic, or hospital for care. Norwegian home care services have seen a significant increase in demand in recent years, which is partly attributable to the ageing population and a trend away from acute hospital treatments toward primary care [3]. The majority of Norwegian home care services are free (publicly financed) and the responsibility of the local government. After the Coordination Reform was passed in 2009 and implemented in 2012 [4], many duties that were traditionally performed by hospitals were assigned to municipalities, who were given more patient accountability.

HCS are Internet of Things (IoT) systems that incorporate, store, and communicate the information gathered by a set of wearable devices and sensors [5]. The implementation of these systems is growing whereby it allows remote patient monitoring to reduce the load at hospitals. This is fundamental to address, since: (1) Hospitals do not have enough beds to accommodate these patients; and according to the Coordination Reform in 2011, tasks were shifted from hospitals to home care services [4] (2) There is a decrease in the number of beds in nursing homes (in Norway) [6]. HCSs collect patients' data, and this (big) data, if properly analyzed, creates helpful knowledge, and can support decision-making. More frequent and inconspicuous monitoring may be more feasible with remote systems (such as blood sugar and cardiac monitoring) than with more traditional types. Early detection of irregularities increases the likelihood that their severity will not worsen, and additionally allows more timely feedback to help service users better manage their own conditions [7,8].

Municipalities cannot set admittance limits for their services because they must guarantee that all residents, regardless of age or disease, receive essential health care [9]. The amount of time available for patient treatment has decreased as a result of the growth in administrative and paperwork needs within home care services throughout this time frame. Both the volume of patient referrals and the complexity of these patients' medical needs have risen because of changing patient demographics and earlier hospital releases. As a result, planning service requirements for home care have become extremely difficult [3].

The current home care workforce is struggling to handle their daily tasks, which employees frequently view as being very unexpected [3]. Staff members at the point of care are expected to do more with the same resources, planning techniques, and capability while being given more tasks that are more complicated and have a wide range in daily volumes [3]. A wide range of intricate tasks are included in the burden of healthcare services [10]. On top of this, there is a staffing deficit for home care services in several European nations [11,12].

In recent years, there has been a significant increase in research activity in the field of remote patient monitoring [13]. To identify basic and complicated behaviors including walking, sitting, running, and other activities of everyday life, activity data gathered using a variety of sensors is analyzed [14]. These activities are crucial for giving caregivers and medical rehabilitation staff real-time feedback regarding patients' behaviors, especially for older and special needs patients [14]. Other key uses are in fall detection and postural recognition [14], where older people are at high risk of falling and where understanding what constitutes a true fall might assist in preventing them due to their tendency to have poor health consequences.

Besides the aforementioned, in healthcare settings where the stakes are high, managing worry and stress on an understaffed team is essential to ensure the team can continue to perform. Burnout among nurses at every level of care is a result of a lack of support and anxiety [15]. Nursing staff can have peace of mind knowing their patients are at home safe, thanks to remote patient monitoring [16]. Remote patient monitoring acts as an extra sense, taking patients out of the hospital with the same quality [17].

Our research aims to leverage Data Analysis and Artificial Intelligence, namely Deep Learning, a common methodology for healthcare problems [18], to remotely gather patient data at home through various devices and machines, including video cameras. Our objective is to develop a decision support system by integrating structured data with images, and sound. This approach enables the extraction of insights for primary stakeholders, such as patients, doctors, carers, and health authorities, offering Decision Support Systems to facilitate informed decision-making and alleviate the workload of home care professionals.

The fusion of data collected remotely, along with structured hospital data, enhances the identification of patterns and findings crucial for personalized treatments. Through the development of a dedicated platform with the required software programs we are able to process all the heterogeneous data sources. Once processed, this data is stored in a Big Data warehouse, establishing an integrated repository for comprehensive analysis. Our Home Care platform incorporates information from various sources, including images from mobile devices, wearables, sound processing, mining, and home devices (e.g., manometers, glucometers, or activity devices via smartwatches). This approach stands in contrast to the typical isolated processing and analysis within proprietary applications offered by respective vendors.

2. Literature Review

2.1. Search Strategy and Inclusion Criteria

In order to assess the work that has been done, we have conducted a literature review. This literature review allows us not only to understand the current state of the art but also to identify gaps or problems on the main topic.

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [7] research methodology has been followed. PRISMA methodology is a widely recognized and accepted method for conducting systematic reviews of literature in healthcare research. It provides a structured approach to identifying, selecting, and analyzing relevant studies, ensuring that all relevant studies captured are related to our research question and providing a transparent and reproducible process for conducting systematic reviews, which can help ensure the quality and rigor of our research. Overall, using the PRISMA methodology, we ensured that a rigorous and comprehensive review of the literature on homecare and remote monitoring systems was conducted.

The research question "What is the state of the art on the usage of Internet of Things in Homecare with Artificial Intelligence" was the base for our literature review.

This review was performed on two databases,such as Scopus and Web of Science Core Collection (WoSCC). The filters applied have ensured that all papers were written in English, had to be articles and were published on the last 6 years (2018–2023).

The research strategy used entailed creating a single question from many research perspectives. By considering the topic, context, and group under analysis, it was possible to identify articles that were included in both databases.

Then we searched, in both databases, all the published work with the concept "Artificial Intelligence" or "Machine Learning" or "Data Mining" or "Data Analytics" or "Data Analysis" or "Neural Networks", the target population "Homecare" or "Care Assistance" or "Remote Monitoring System" within a context of "Internet of Things" or "Big Data". Our final query was: "("Artificial Intelligence" OR "Machine Learning" OR "data mining" OR "Data Analytics" OR "Data Analysis" OR "neural networks") AND (Home care OR "Homecare" OR "care assistance" OR "remote monitoring system") AND (IoT OR "Internet of Things" OR "big data")".

The output of the query resulted in 108 documents, but after removing duplicates, we managed to have 77 distinct documents that composed all the papers that should be analyzed. To represent the analysis of all the papers read, a PRISMA process diagram was created in Figure 1.

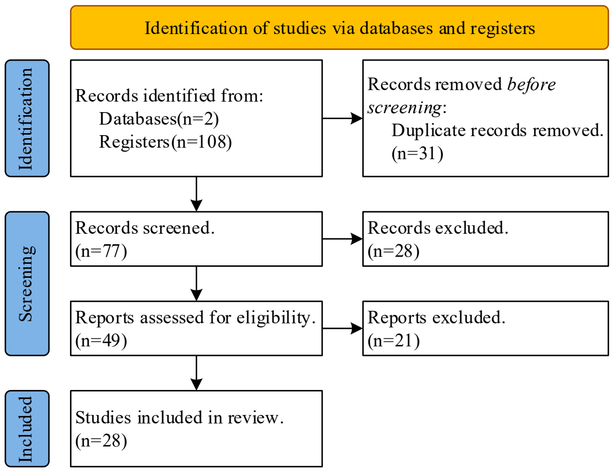

Figure 1. Results of the application of PRISMA methodology.

The purpose of this literature review is to understand what exists of homecare, the problems and benefits identified and what can be done to improve the quality of remote monitoring systems to allow patients without serious diseases to go home and be monitored remotely. All the medical staff would benefit from the relief of workload, and patients also could have a better quality of life if they were allowed to be at home. The main topics discussed in all articles are shown in Table 1, with focus on ML and IoT as roles to achieve functional and efficient remote monitoring systems.

2.2. Goals and Outcomes Analysis

In our comprehensive review, we systematically analyzed each of the main goals, presenting the findings in Figure 2.

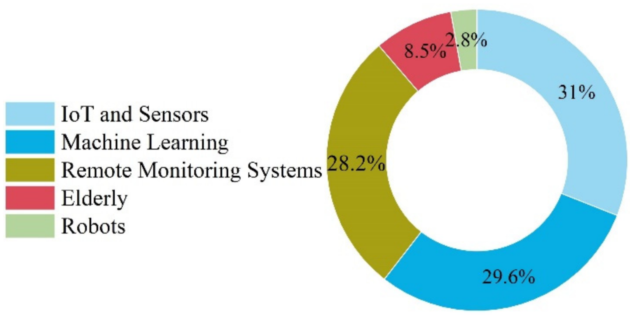

Figure 2. Comprehensive analysis of each topic, for all relevant papers.

The detailed summary of the papers can be found in Table 1, where each topic is associated with its respective references and the number of papers covered.

Table 1. Main areas of relevant papers identified.

Topics	References	No. Papers
IoT and Sensors	[19–40]	22
Machine Learning	[19–31,33–40]	21
Remote Monitoring Systems	[19–31,38–44]	20
Elderly	[38–43]	6
Robots	[45,46]	2

Articles [19–31] discuss the use of Machine Learning (ML) and/or wearable sensors in order to monitor and help self-diagnose some diseases allowing the patients to be remote monitored. Systems aim to monitor mainly heart diseases, but there are other examples that monitor Metabolic Syndrome, sleep monitoring, diabetes, cerebral palsy, or Parkinson disease. With the same scope but more focused on elderly individuals, refs [41–43] propose systems for monitoring and management of home care elderly adults with focus on elderly needs and acceptance. New solutions are discussed in order to balance the needs of elderly people and the management of their health, but studies show improved quality of life for older people when they are at home being monitored. One solution proposed home interactive elderly care two-way video healthcare system that would help the medical staff manage their effort.

Article [32] proposes a review of wireless sensor network health monitoring systems and the conclusions are encouraging with the development of more flexible, reliable, secure, real-time and energy efficient systems that improve the quality of remote monitoring systems. Refs. [33–37] discuss and improve the utilization of IoT and sensors in Homecare. They prevent the detection of anomalies in the data stream created with IoT sensors and propose ML models that make effective and timely decisions in the healthcare domain. Overall, sensors are more accurate and efficient with gaps being analyzed and combated.

Another main topic is explored by [38–40], where IoT and ML take a major role in elderly fall prediction and activity recognition. Using sensors or cameras, results appear to be very good.

From another point of view, [45,46] suggest the use of robots that would provide valuable tools for in-home care services. In [44] emerge as a caller for the urgent need for home-based remote monitoring systems to avoid the collapse of hospitals' first line.

A lot of things have been done to improve the performance of remote monitoring systems allowing patients to, if possible, be at home and keep being monitored from possible health problems that could have.

In summary, many studies are focused on the patient side, allowing them to be monitored remotely, but there's a lack of concern on the caregivers and medical staff side. This point is relevant because it places our study on a scientific gap. With these solutions, we can improve the efficiency of medical staff job by reducing the workload. In a world where Hospitals suffer from overload, it's crucial to give conditions to medical staff and caregivers so they can have a better life quality and increase their proficiency. In fact, with the solutions presented in the literature review, we can address different needs from different perspectives.

3. Materials and Methods

Care processes digitalization, holistic sensing supported by the Internet of Things (IoT) system and AI tools are being actively applied to the health sector giving rise to the smart health paradigm [47]. In this transformative process, the Health Remote Monitoring Systems (HRMS) are recognized as an emerging technology [48], using sensors and wearable devices to collect patient's data. However, to present clinical value these systems have to be associated with clear clinical processes and therapeutics, so the measurements could be linked with actual patient care.

The implementation of HRMS is based on a health related IoT system that incorporates, stores, and communicates the information gathered by a set of wearable devices and sensors, video and image [49]. The computer senses and records the daily physiological data of the patient by means of a data processing device, data transition, data archive, data analytics, and AI [50]. The HRMS is based on four main pillars and aims. Firstly, to develop a system to identify disease development and disease prevention through the use of remote sensors. Secondly, big data processing and analysis is used to process multiple heterogeneous data sources in order to process different patient data and provide high-quality personalized treatment. Thirdly, prediction models built by Artificial Intelligence can be implemented on top of the processed data from Big Data, which would allow the classification of patients, discovering of behavioral patterns. Through this process, alerts can be generated when an abnormality is registered in order to help with disease prevention. Lastly, to create a remote interaction process from hospitals to the patients. Therefore, HRMS enables a data-intensive approach, in which a large amount of health data is generated, stored, and available for data mining, allowing for the generation of useful knowledge.

The device's communication with cloud platforms allows for these sensing data to be stored in the cloud and easily accessed by doctors, allowing a range of remote health monitoring functions. Remote Patient Monitoring (RPM) Technologies require machinery that collects and interprets biometric & physiological data [50]. RPM has many applications such as real-time illness detection (through the generation of alerts when an abnormality is registered) [51], continuous monitorization of patients such as those with chronic disease or less severe conditions (reducing patient load at hospitals, as it allows recovering of non-critical patients to happen in their homes) or athlete health monitorization [50].

Considering the current state of art, this research work proposes an AI-based solution using data, image, and sound:

- The ability to take images using standard smartphone technology as a simple sensing tool and the creation of an image data repository;
- Fusion of different data sources (data, image, and sound) in a big data for different chronic diseases and we propose to validate in dementia cases;
- Present meaningful and useful data to decision makers to support improved interventions;
- Participatory process involving end-users using hospital and AA patients.

It is widely recognized that dementia needs to be seriously considered, and more remote monitor solutions with AI, like the ones proposed in this project, are required in order to reduce the future impact of these diseases in the forthcoming years in the EU and improve the quality of life of these patients. The research introduces a remote monitoring system designed to assist caregivers in minimizing their workload. Leveraging AI and data analytics, this system facilitates well-informed decision-making. By consistently monitoring patients, it generates alerts whenever attention is needed, thereby enhancing the efficiency of caregivers and reducing their overall workload.

3.1. Research Strategy

Action Research has been defined to bridge the gap between research and practice. With this aim, it has two clear goals: to generate profits for the customer of the research; and, at the same time, to generate relevant "knowledge of research" [52]. Therefore, Action-Research is an approach highly collaborative between research, researchers, and practitioners, focused on both theory and practice and carried out by means of a cyclic process. In addition, Action-Research describes a class of methods, which share the following characteristics [53]: (1) To be oriented to action and change; (2) To be focused on a problem; (3) To have an organic model of process that entails systematic stages and some iterative ones; and 4) To be collaborative between the participants.

In a more formal analysis of the participants, Action-Research, Ref. [54] identifies four types of roles that are described in the following along with their related actors.

Considering the above-assigned responsibilities, in order to put the Action-Research methodology into practice, it is necessary to establish the activities that will guide the research. We proposed a highly flexible Big Data architecture and the creation of several dashboards for relevant stakeholders following the methodology. This approach [55] elucidates the specific requirements for each stakeholder, and ensures that they implement dashboards that are tailored to different roles and users, being able to derive multiple sets of dashboards that are aligned with the identified information needs.

3.2. Methods

Information Communications and Technology (ICT) solutions for healthcare are mostly focused on telehealth platforms designed for adaptive and proactive needs. For these systems to be interoperable, usable, secure, and accurate, strong integration is required. We propose a remote solution that can analyze structured data, video, and sound because these are components of daily life. Sound and video can be acquired with a camera, and for privacy issues, we do not store them. Everything is processed locally. Our HCS is depicted in Figure 3. In this system, all data is stored in a cloud server, providing medical staff with access to it. Even though all image processing occurs locally, the server stores the output, such as the patient's detected emotion.

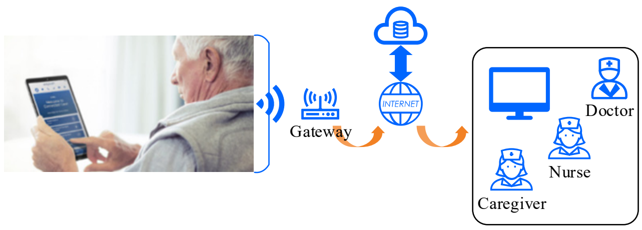

Figure 3. Proposed System.

In terms of structured data, we have access to biometric information such as temperature, heart rate, and oximetry. All the data was generated in a laboratory setting. As illustrated in Figure 4, we observe the oscillation in a patient's temperature throughout the day, and their heart rate is depicted in Figure 5.

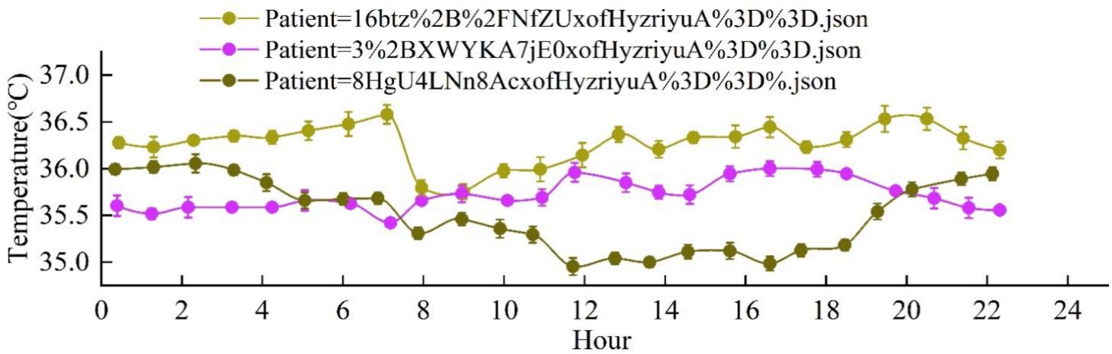

Figure 4. Daily rhythm of body temperature of three different patients.

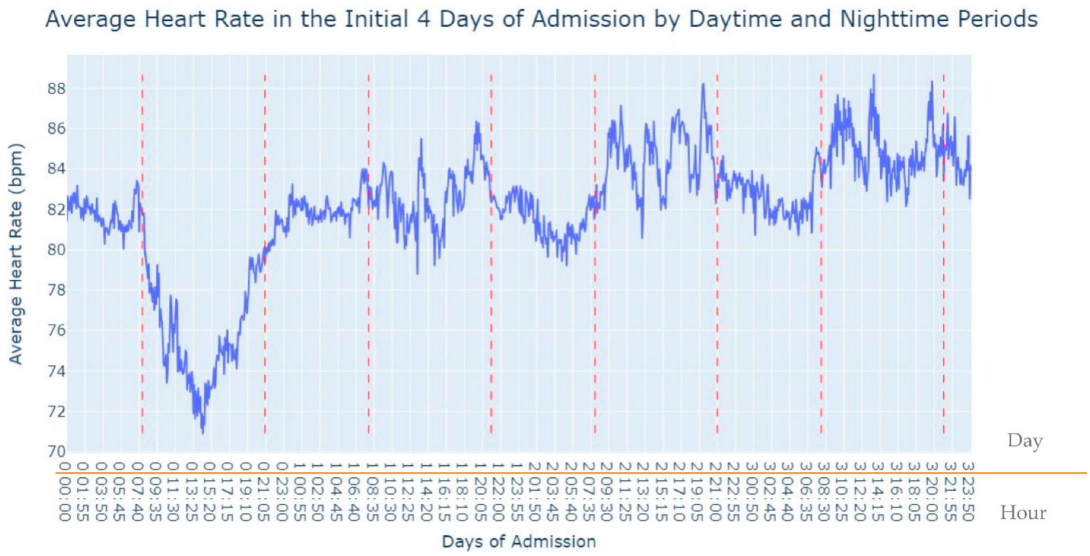

Figure 5. Average Heart Rate (y) by day/hour (x).

Our primary objective with this dataset is to predict abnormal values. To achieve this, we employed a 30-minute interval (determined through autocorrelation) for making such predictions. This approach enables us to anticipate an outlier 30 minutes before its occurrence. In the prediction of abnormal values for heart rate, we tested several models, including KNN, Random Forest, Logistic Regression, SVM, Naïve Bayes, and Neural Networks. Among these, Neural Networks demonstrated the best result, achieving an accuracy of 94%, as illustrated in Figure 6.

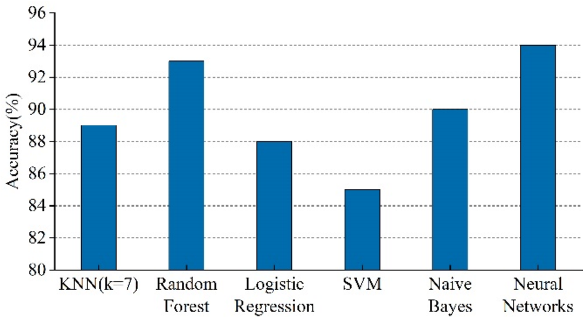

Figure 6. Algorithm's Performance.

Every time an outlier is registered, an email is sent to the caregivers, as exemplified in Figure 7.

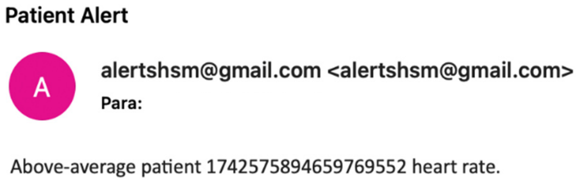

Figure 7. Alert system message.

Based on video data processing from daily/weekly conversations

1) Face monitor process—Trained algorithm to recognize facial expressions like: disgust, happiness, sadness, surprise, anger, fear, and contempt;
2) Head pose detection—We detected three head poses including yaw, pitch, and roll, using the pre-trained OpenFace deep neural network tool;
3) Posture recognition—To recognize patient posture, we used a multi-person pose estimation model to localize the anatomical key points of joints and limbs. Then we used the lengths of body limbs and their relative angles as features for recognizing lying in bed, standing, sitting on the bed, and sitting in the chair;
4) Room sound pressure levels and light intensity - The sound pressure levels for delirious patients' rooms during the night were on average higher than the sound pressure levels of non-delirious patients' rooms. Average night-time sound pressure levels were significantly different between the delirious and non-delirious patients (p-value < 0.05).

For the Face monitor process implementation, we have developed a CNN with the public datasets available like FER2013 [56], CK+ [57], and AffectNet [58], where we have merged them into one dataset like the work presented in [59]. We have tested this implementation in a private dataset produced by the authors of this article, where the model has achieved 87.6% accuracy in identifying the different emotions.

The model that we have developed comprises a series of convolutional layers, pooling layers, a flatten layer, fully connected layers, and an output layer. Three convolutional layers with kernel sizes of (3, 3) are employed to perform feature extraction from the input images. The first convolutional layer includes 32 filters, followed by 64 filters in the second layer, and 128 filters in the third layer. This increment in the number of filters enables the model to capture increasingly complex spatial features. Max-pooling layers with a pool size of (2, 2) are incorporated after each convolutional layer. These layers downsample the spatial dimensions, retaining the most salient features while reducing computational complexity. Following the convolutional and pooling layers, a flatten layer is introduced to transform the three-dimensional tensor output into a one-dimensional tensor, preparing the data for the subsequent fully connected layers. A densely connected layer with 256 units and a Rectified Linear Unit (ReLU) activation function is introduced to capture high-level features derived from the flattened representation. To mitigate overfitting, a dropout layer with a dropout rate of 0.3 is incorporated. The final layer is a fully connected layer with a softmax activation function. It produces the model's predictions across multiple emotion classes, with the number of units corresponding to the total number of emotion categories. The model summarization is depicted in Figure 8.

Layer(type)	Output Shape	Param #
Conv2d_3 (Conv2D)	(None, 46, 46, 32)	320
max_pooling2d_3 (MaxPoolin g2D)	(None, 23, 23, 32)	0
conv2d_4 (Conv2D)	(None, 21, 21, 64)	18496
max_pooling2d_ 4 (MaxPoolin g2D)	(None, 10, 10, 32)	0
conv2d_5 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_5 (MaxPoolin g2D)	(None, 2048)	0
Flatten_1 (Flatten)	(None, 256)	0
dense_1 (Dense)	(None, 256)	524544
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 7)	1799

Total params : 619015 (2.36 MB)

Trainable p arams: 619015 (2.36 MB)

Non-trainable params: 0 (0.00 Byte)

Figure 8. Model Summarization.

Regarding head pose detection our healthcare monitoring system, aims to identify and analyze the orientation of a patient's head in three-dimensional space. This involves estimating three key angles: yaw (rotation around the vertical axis), pitch (rotation around the lateral axis), and roll (rotation around the longitudinal axis).

To implement this functionality, we have used the pre-trained OpenFace[60] deep neural network tool, a widely-used resource for facial behavior analysis. The OpenFace model comes equipped with the ability to detect facial landmarks, which are essential for accurate head pose estimation. In the implementation process, we collect input data in the form of images (video frames) that contain patients' faces.

The implementation involved loading the pre-trained OpenFace model and feeding the preprocessed facial images into the model for landmark detection. The detected landmarks are then utilized to calculate the patient's head pose angles, including yaw, pitch, and roll. The output of this process is a set of estimated head pose angles corresponding to each detected face in the input data. This information is then stored into the database of the monitoring system, allowing us to associate head pose details with other relevant patient data. This information can be valuable for assessing patient engagement, attentiveness, or potential discomfort.

For posture recognition we have used Movenet [61], a real-time pose estimation model developed by Google. Movenet is designed to accurately and efficiently estimate human body poses from images or video frames. The key characteristic of Movenet is its ability to provide pose estimates for multiple people in real-time, making it suitable for applications such as fitness tracking, gesture recognition, and augmented reality. This model produces a compact representation of body poses using a set of key points, making it useful for applications where only key joint locations are required.

A new strategy called pervasive computing [62] focuses on creating intelligent settings where connected devices are inserted and provide continuous, dependable, non-intrusive connectivity with extra benefits. Without a clear understanding of the underlying technological interplay, this system's effect is often an enhancement in human experience and quality of life [63]. As a result, ubiquitous data can also be thought of as information that is always accessible. The whole information required to do an assessment is not always available in critical contexts, such as intensive care units, where choices must be made at the appropriate moment. Despite the fact that not all medical errors may be avoided, the spread of data can be facilitated through ubiquitous data techniques. Reducing redundant information and allowing it to be kept on mobile devices or in strategically placed devices near where choices will be made will improve the quality of healthcare [64]. The system that sends alarms from the monitoring patient system is an example of pervasive data. When patients are outside the parameters of the monitored qualities, these notifications are sent. In general, ubiquitous healthcare aids medical professionals by establishing a setting that enables them to access information at anytime and anyplace.

4. Conclusions

Considering the rapid advancements in AI and associated technologies, it is evident that these developments can significantly assist healthcare providers in improving patient care and optimizing operational processes. This study specifically investigated the impact of AI technology, utilizing data fusion, on remote chronic patient care. The study has demonstrated promising results, since it has achieved 94% accuracy in the prediction of abnormal values for heart rate using Neural Networks, and 87.6% for Facial Expression classification using Convolutional Neural Networks.

The successful management of these opportunities and challenges necessitates collaborative efforts and determination from all stakeholders within the healthcare industry. In conclusion, our research demonstrates that AI in remote home care monitoring systems can alleviate the workload of caregivers by monitoring the patients and generating alerts when attention is required. By automating the extraction and analysis of pertinent information from large volumes of unstructured data, these systems empower healthcare professionals to make more informed decisions, enhance patient outcomes, and mitigate the manual workload of data entry and analysis.

As the market for wearable medical devices and remote home care systems continues to expand, the integration of AI is poised to become increasingly prevalent in the healthcare sector. This shift presents new prospects for advancing patient care and relieving the workload on healthcare providers.

In light of the current state of the art, it is noteworthy that while numerous studies focus on monitoring patients remotely, there remains a significant gap in addressing the needs of caregivers and medical staff. Our study fills this gap by emphasizing the importance of improving the efficiency of medical staff through workload reduction. In a healthcare landscape often burdened by overload, it is imperative to enhance the quality of life for medical staff and caregivers, thereby boosting their proficiency. The solutions presented in the literature review address diverse needs from various perspectives, offering a holistic approach to healthcare challenges.

5. Future Work

For future work, we aim to implement the system illustrated in Figure 9, in a Big Data Setting where we collect questionaries from the patients and merge the data with Electronic Health Records. Also, by detecting Action Units (AU) from the video, we can add value from the expressions detected by our model, doing better and more accurate classifications and predictions. Correlating this data with actigraphy analysis, in the future can be fruitful, since analyzing sleep parameters, time and activity parameters, can correlate with some health events of the individual. Additionally, a crucial aspect for further exploration is extremity movement analysis. This involves examining data from three accelerometer sensors placed on the patient's wrist, ankle, and arm, and comparing the results between delirious and non-delirious patients. Such analysis holds the potential for providing valuable insights into patient conditions and facilitating more targeted and personalized care strategies. While the current implementation collects head pose data, its practical applications within the healthcare monitoring system are yet to be explored. The recorded head pose information presents promising opportunities for enhancing patient care and healthcare workflows. The following applications could be considered for future work:

- Patient Comfort Assessment: Investigate the correlation between head pose patterns and patient comfort levels. Develop algorithms or models that can automatically detect signs of discomfort or unease based on changes in head orientation. This can lead to interventions aimed at improving the overall patient experience.
- Engagement and Communication Analysis: Explore how head pose data can be integrated with communication analytics to provide a comprehensive understanding of patient engagement during telehealth interactions. Develop metrics or indices that quantify patient attentiveness or potential communication challenges based on head pose information.
- Early Detection of Health Issues: Research and identify specific health conditions or symptoms that may manifest through alterations in head pose patterns. Develop predictive models that leverage head pose data to provide early warnings or alerts for potential health issues, facilitating timely intervention.
- Personalized Care Strategies: Investigate the incorporation of head pose information into the development of personalized care plans. Explore how head pose patterns, when analyzed alongside other health parameters, can contribute to tailoring healthcare interventions to individual patient needs and preferences.

- Improved Telehealth Experience: Enhance the telehealth experience by utilizing head pose data to optimize virtual interactions. Develop features or functionalities that dynamically adjust the virtual environment based on patient head orientation, fostering a more engaging and effective telehealth setting.
- Efficient Healthcare Workflow: Investigate the integration of head pose data into the healthcare workflow to improve efficiency. Explore the potential for prioritizing alerts or communications based on observed head poses, directing attention to situations where immediate intervention or communication may be warranted.

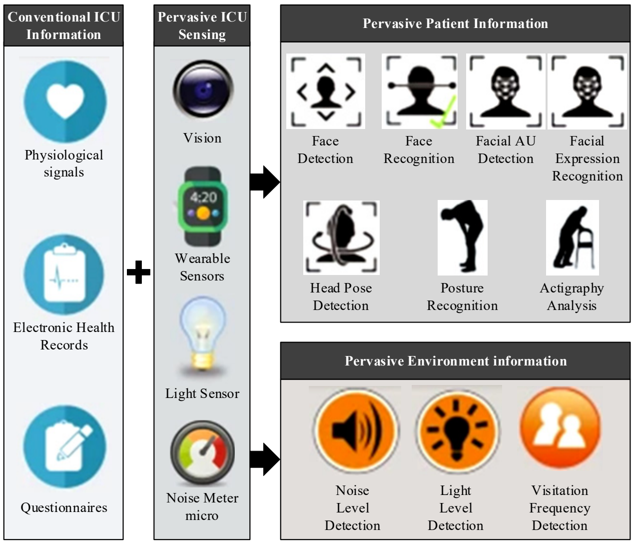

Figure 9. Proposed system for Future Work.

Author Contributions
Conceptualization (L.B.E. and J.C.F.), Methodology (L.B.E. and M.N,), Validation (L.B.E. and J.C.F.), Data Curation (M.N.), Writing—original draft preparation (M.N.), Writing—review and editing (L.B.E., M.N., B.I.H. and J.C.F.), Supervision (L.B.E. and J.C.F.), Funding Acquisition (J.C.F.). All authors have read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Conflict of Interest Statement
The authors declare that they have no conflict of interest.

Data Availability Statement
Not applicable.

References

1. Eurostat, 'Europe in figures - Eurostat yearbook 2008', Luxembourg, Office for Official Publications of the European Communities, 2008. Accessed: Sep. 06, 2022. [Online]. Available: https://ec.europa.eu/eurostat/web/products-statistical-books/-/ks-cd-07-001
2. R. Tarricone and A. D. Tsouros, *Home care in Europe: the solid facts*. World Health Organization. Regional Office for Europe, 2008. Accessed: Sep. 06, 2022. [Online]. Available: https://apps.who.int/iris/handle/10665/328766
3. B. I. Helgheim, B. E. Sandbaek, and L. Slyngstad, 'A prospective investigation of direct and indirect home care activities in three rural Norwegian municipalities', *BMC Health Serv. Res.*, vol. 18, no. 1, p. 977, Dec. 2018, doi: 10.1186/s12913-018-3794-2.
4. Norwegian Ministry of Health and Care Services, 'The Coordination Reform', Oslo: The Norwegian Government, 2009.
5. K. Banti, M. Louta, and P. Baziana, 'Data Quality in Human-Centric Sensing-Based Next-Generation IoT Systems: A Comprehensive Survey of Models, Issues, and Challenges', *IEEE Open J. Commun. Soc.*, vol. 4, pp. 2286–2317, 2023, doi: 10.1109/OJCOMS.2023.3316118.
6. 'Helse- og omsorgstjenester i KPR', Helsedirektoratet. Accessed: Sep. 08, 2022. [Online]. Available: https://www.helsedirektoratet.no/statistikk/helse-omsorgstjenester-i-KPR
7. R. A. Clark, S. C. Inglis, F. A. McAlister, J. G. F. Cleland, and S. Stewart, 'Telemonitoring or structured telephone support programmes for patients with chronic heart failure: systematic review and meta-analysis', *BMJ*, vol. 334, no. 7600, p. 942, May 2007, doi: 10.1136/bmj.39156.536968.55.
8. M. Jaana and G. Paré, 'Home telemonitoring of patients with diabetes: a systematic assessment of observed effects', *J. Eval. Clin. Pract.*, vol. 13, no. 2, pp. 242–253, Apr. 2007, doi: 10.1111/j.1365-2753.2006.00686.x.
9. Norwegian Ministry of Health Care and Service, 'Health and Care Services Act. ACT-2012-06-22-46', Oslo: The Norwegian Government, 2011.
10. A. S. Morris, J. S. Silk, L. Steinberg, S. S. Myers, and L. R. Robinson, 'The Role of the Family Context in the Development of Emotion Regulation', *Soc. Dev. Oxf. Engl.*, vol. 16, no. 2, pp. 361–388, May 2007, doi: 10.1111/j.1467-9507.2007.00389.x.
11. R. J. V. Montgomery, P. Lyn Holley, J. Deichert, and K. Kosloski, 'A Profile of Home Care Workers From the 2000 Census: How It Changes What We Know', *The Gerontologist*, vol. 45, no. 5, pp. 593–600, Oct. 2005, doi: 10.1093/geront/45.5.593.
12. S. Hussein and J. Manthorpe, 'An International Review of the Long-Term Care Workforce', *J. Aging Soc. Policy*, vol. 17, no. 4, pp. 75–94, Nov. 2005, doi: 10.1300/J031v17n04_05.
13. 'Smart homes and home health monitoring technologies for older adults: A systematic review - PubMed'. Accessed: Nov. 02, 2022. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/27185508/
14. H. F. Nweke, Y. W. Teh, G. Mujtaba, and M. A. Al-garadi, 'Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions', *Inf. Fusion*, vol. 46, pp. 147–170, Mar. 2019, doi: 10.1016/j.inffus.2018.06.002.
15. C. Dall'Ora, J. Ball, M. Reinius, and P. Griffiths, 'Burnout in nursing: a theoretical review', *Hum. Resour. Health*, vol. 18, no. 1, p. 41, Jun. 2020, doi: 10.1186/s12960-020-00469-9.
16. N. Gale and H. Sultan, 'Telehealth as "peace of mind": embodiment, emotions and the home as the primary health space for people with chronic obstructive pulmonary disorder', *Health Place*, vol. 21, pp. 140–147, May 2013, doi: 10.1016/j.healthplace.2013.01.006.
17. O. S. Albahri, A. A. Zaidan, B. B. Zaidan, M. Hashim, A. S. Albahri, and M. A. Alsalem, 'Real-Time Remote Health-Monitoring Systems in a Medical Centre: A Review of the Provision of Healthcare Services-Based Body Sensor Information, Open Challenges and Methodological Aspects', *J. Med. Syst.*, vol. 42, no. 9, p. 164, Jul. 2018, doi: 10.1007/s10916-018-1006-6.
18. V. Sharma, A. Bajaj, and A. Abraham, 'Machine Learning Techniques for Electronic Health Records: Review of a Decade of Research.', *Int. J. Comput. Inf. Syst. Ind. Manag. Appl.*, vol. 15, pp. 595–604, Jan. 2023.
19. T. Zhou, Y. Zhang, C. Wu, C. Shen, J. Li, and Z. Liu, 'An Augmented Model with Inferred Blood Features for the Self-diagnosis of Metabolic Syndrome', *METHODS Inf. Med.*, vol. 59, no. 01, pp. 18–30, Feb. 2020, doi: 10.1055/s-0040-1710382.
20. F. Miao, X. Wang, L. Yin, and Y. Li, 'A Wearable Sensor for Arterial Stiffness Monitoring Based on Machine Learning Algorithms', *IEEE Sens. J.*, vol. 19, no. 4, pp. 1426–1434, Feb. 2019, doi: 10.1109/JSEN.2018.2880434.

21. P.-Y. Jeng, L.-C. Wang, C.-J. Hu, and D. Wu, 'A Wrist sensor sleep posturemonitoring system: An automatic labeling approach', *Sens. Switz.*, vol. 21, no. 1, pp. 1–19, 2021, doi: 10.3390/s21010258.
22. A. F. Hussein, N. Arun Kumar, M. Burbano-Fernandez, G. Ramirez-Gonzalez, E. Abdulhay, and V. H. C. De Albuquerque, 'An automated remote cloud-based heart rate variability monitoring system', *IEEE Access*, vol. 6, pp. 77055–77064, 2018, doi: 10.1109/ACCESS.2018.2831209.
23. S. Raj, 'An Efficient IoT-Based Platform for Remote Real-Time Cardiac Activity Monitoring', *IEEE Trans. Consum. Electron.*, vol. 66, no. 2, pp. 106–114, 2020, doi: 10.1109/TCE.2020.2981511.
24. G. Premalatha and V. T. Bai, 'Design and implementation of intelligent patient in-house monitoring system based on efficient XGBoost-CNN approach', *Cogn. Neurodyn.*, vol. 16, no. 5, pp. 1135–1149, 2022, doi: 10.1007/s11571-021-09754-2.
25. M. A. Serhani, H. T. El Kassabi, H. Ismail, and A. N. Navaz, 'ECG monitoring systems: Review, architecture, processes, and key challenges', *Sens. Switz.*, vol. 20, no. 6, 2020, doi: 10.3390/s20061796.
26. R. Basatneh, B. Najafi, and D. G. Armstrong, 'Health Sensors, Smart Home Devices, and the Internet of Medical Things: An Opportunity for Dramatic Improvement in Care for the Lower Extremity Complications of Diabetes', *J. Diabetes Sci. Technol.*, vol. 12, no. 3, pp. 577–586, 2018, doi: 10.1177/1932296818768618.
27. N. J. Conn, K. Q. Schwarz, and D. A. Borkholder, 'Nontraditional electrocardiogram and algorithms for inconspicuous in-home monitoring: Comparative study', *JMIR MHealth UHealth*, vol. 6, no. 5, 2018, doi: 10.2196/mhealth.9604.
28. D. N. Singh, M. F. Hashmi, and S. K. Sharma, 'Predictive analytics & modeling for modern health care system for cerebral palsy patients', *Multimed. Tools Appl.*, vol. 79, no. 15–16, pp. 10285–10307, 2020, doi: 10.1007/s11042-019-07834-4.
29. T. Shaik *et al.*, 'Remote patient monitoring using artificial intelligence: Current state, applications, and challenges', *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, 2023, doi: 10.1002/widm.1485.
30. R. Luis-Martínez, M. H. G. Monje, A. Antonini, Á. Sánchez-Ferro, and T. A. Mestre, 'Technology-Enabled Care: Integrating Multidisciplinary Care in Parkinson's Disease Through Digital Technology', *Front. Neurol.*, vol. 11, 2020, doi: 10.3389/fneur.2020.575975.
31. H. Bolhasani, M. Mohseni, and A. M. Rahmani, 'Deep learning applications for IoT in health care: A systematic review', *Inform. Med. Unlocked*, vol. 23, 2021, doi: 10.1016/j.imu.2021.100550.
32. G. Salunke, V. Singh, and C. Jadhav, 'A Review Approach to Modeling, Analysis, and Design Framework for Wireless Sensor Network Health Monitoring Systems', *J. Pharm. Negat. RESULTS*, vol. 13, pp. 165–177, 2022, doi: 10.47750/pnr.2022.13.S02.24.
33. S. Kaya, A. Erdem, and A. Gunes, 'A Smart Data Pre-Processing Approach to Effective Management of Big Health Data in IoT Edge', *SMART HOMECARE Technol. TELEHEALTH*, vol. 8, pp. 9–21, 2021, doi: 10.2147/SHTT.S313666.
34. H. Fouad, A. S. Hassanein, A. M. Soliman, and H. Al-Feel, 'Analyzing patient health information based on IoT sensor with AI for improving patient assistance in the future direction', *Meas. J. Int. Meas. Confed.*, vol. 159, 2020, doi: 10.1016/j.measurement.2020.107757.
35. Y. Mao, L. Zhang, and X. Wu, 'Perception Analysis and Early Warning of Home-Based Care Health Information Based on the Internet of Things', *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/6634575.
36. F. Tiersen *et al.*, 'Smart home sensing and monitoring in households with dementia: User-centered design approach', *JMIR Aging*, vol. 4, no. 3, 2021, doi: 10.2196/27047.
37. A. Grgurić, M. Mošmondor, and D. Huljenić, 'The smarthabits: An intelligent privacy-aware home care assistance system', *Sens. Switz.*, vol. 19, no. 4, 2019, doi: 10.3390/s19040907.
38. P. Kulurkar, C. K. Dixit, V. C. Bharathi, A. Monikavishnuvarthini, A. Dhakne, and P. Preethi, 'AI based elderly fall prediction system using wearable sensors: A smart homecare technology with IOT', *Meas. Sens.*, vol. 25, 2023, doi: 10.1016/j.measen.2022.100614.
39. T. Vaiyapuri, E. L. Lydia, M. Y. Sikkandar, V. G. Diaz, I. V. Pustokhina, and D. A. Pustokhin, 'Internet of Things and Deep Learning Enabled Elderly Fall Detection Model for Smart Homecare', *IEEE Access*, vol. 9, pp. 113879–113888, 2021, doi: 10.1109/ACCESS.2021.3094243.
40. J. Jansson and I. Hakala, 'Managing sensor data streams in a smart home application', *Int. J. Sens. Netw.*, vol. 32, no. 4, pp. 247–258, 2020, doi: 10.1504/IJSNET.2020.106603.
41. B. Zhang *et al.*, 'A Framework for Remote Interaction and Management of Home Care Elderly Adults', *IEEE Sens. J.*, vol. 22, no. 11, pp. 11034–11044, 2022, doi: 10.1109/JSEN.2022.3170295.
42. C. M. Timon *et al.*, 'Development of an Internet of Things Technology Platform (the NEX System) to Support Older Adults to Live Independently: Protocol for a Development and Usability Study', *JMIR Res. Protoc.*, vol. 11, no. 5, 2022, doi: 10.2196/35277.
43. R. Miranda *et al.*, 'Improved quality of care and reduced healthcare costs at the end-of-life among older people with dementia who received palliative home care: A nationwide propensity score-matched decedent cohort study', *Palliat. Med.*, vol. 35, no. 9, pp. 1701–1712, Oct. 2021, doi: 10.1177/02692163211019321.
44. G. Castelnuovo, G. Pietrabissa, G. M. Manzoni, F. Sicurello, I. Zoppis, and E. Molinari, 'Fighting the COVID-19 pandemic using the technology-based second-line in Italy and Lombardy: The urgent need of home-based remote monitoring systems to avoid the collapse of the hospital-centred first line', *J. Glob. Health*, vol. 10, no. 2, pp. 1–2, 2020, doi: 10.7189/jogh.10.020371.
45. G. Yang *et al.*, 'Homecare Robotic Systems for Healthcare 4.0: Visions and Enabling Technologies', *IEEE J. Biomed. Health Inform.*, vol. 24, no. 9, pp. 2535–2549, Sep. 2020, doi: 10.1109/JBHI.2020.2990529.
46. H. Zhao *et al.*, 'Intelligent indoor metasurface robotics', *Natl. Sci. Rev.*, doi: 10.1093/nsr/nwac266.
47. A. Holzinger, C. Röcker, and M. Ziefle, 'From Computer Innovation to Human Integration: Current Trends and Challenges for Pervasive HealthTechnologies', in *Pervasive Health, Human-Computer Interaction*, London: Springer, 2014, pp. 1–17.

48. O. S. Albahri *et al.*, ‘Systematic Review of Real-time Remote Health Monitoring System in Triage and Priority-Based Sensor Technology: Taxonomy, Open Challenges, Motivation and Recommendations’, *J. Med. Syst.*, vol. 42, no. 5, p. 80, Mar. 2018, doi: 10.1007/s10916-018-0943-4.
49. M. Alshamrani, ‘IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey’, *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 8, Part A, pp. 4687–4701, Sep. 2022, doi: 10.1016/j.jksuci.2021.06.005.
50. L. P. Malasinghe, N. Ramzan, and K. Dahal, ‘Remote patient monitoring: a comprehensive study’, *J. Ambient Intell. Humaniz. Comput.*, vol. 10, no. 1, pp. 57–76, Jan. 2019, doi: 10.1007/s12652-017-0598-x.
51. L. B. Elvas, M. Nunes, J. C. Ferreira, M. S. Dias, and L. B. Rosário, ‘AI-Driven Decision Support for Early Detection of Cardiac Events: Unveiling Patterns and Predicting Myocardial Ischemia’, *J. Pers. Med.*, vol. 13, no. 9, Art. no. 9, Sep. 2023, doi: 10.3390/jpm13091421.
52. N. Kock, ‘Information systems action research: Serving two demanding masters’, *Inf. Technol. People*, vol. 14, Mar. 2001, doi: 10.1108/itp.2001.16114aaa.001.
53. R. Baskerville and T. Wood-Harper, ‘A Critical Perspective on Action Research as a Method for Information Systems Research’, *J. Inf. Technol.*, vol. 11, pp. 235–246, Sep. 1996, doi: 10.1080/026839696345289.
54. Y. Wadsworth, *What is participatory action research?* Action Research Issues Association, 1993.
55. A. Lavalle, A. Maté, and J. Trujillo, ‘Requirements-Driven Visualizations for Big Data Analytics: A Model-Driven Approach’, in *Conceptual Modeling*, A. H. F. Laender, B. Pernici, E.-P. Lim, and J. P. M. de Oliveira, Eds., in Lecture Notes in Computer Science. Cham: Springer International Publishing, 2019, pp. 78–92. doi: 10.1007/978-3-030-33223-5_8.
56. I. J. Goodfellow *et al.*, ‘Challenges in Representation Learning: A Report on Three Machine Learning Contests’, in *Neural Information Processing*, M. Lee, A. Hirose, Z.-G. Hou, and R. M. Kil, Eds., in Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2013, pp. 117–124. doi: 10.1007/978-3-642-42051-1_16.
57. P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, ‘The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression’, in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*, Jun. 2010, pp. 94–101. doi: 10.1109/CVPRW.2010.5543262.
58. ‘AffectNet – Mohammad H. Mahoor, PhD’. Accessed: Mar. 04, 2024. [Online]. Available: http://mohammadmahoor.com/affectnet/
59. J. H. Kim, A. Poulose, and D. S. Han, ‘The Extensive Usage of the Facial Image Threshing Machine for Facial Emotion Recognition Performance’, *Sensors*, vol. 21, no. 6, Art. no. 6, Jan. 2021, doi: 10.3390/s21062026.
60. ‘OpenFace’. Accessed: Mar. 04, 2024. [Online]. Available: https://cmusatyalab.github.io/openface/
61. ‘Pose estimation | TensorFlow Lite’, TensorFlow. Accessed: Mar. 04, 2024. [Online]. Available: https://www.tensorflow.org/lite/examples/pose_estimation/overview
62. D. Saha, A. Mukherjee, and S. Bandyopadhyay, ‘Pervasive Computing’, in *Networking Infrastructure for Pervasive Computing: Enabling Technologies and Systems*, D. Saha, A. Mukherjee, and S. Bandyopadhyay, Eds., Boston, MA: Springer US, 2003, pp. 1–37. doi: 10.1007/978-1-4615-1143-4_1.
63. S. Park and S. Jayaraman, ‘Enhancing the quality of life through wearable technology’, *IEEE Eng. Med. Biol. Mag.*, vol. 22, no. 3, pp. 41–48, May 2003, doi: 10.1109/MEMB.2003.1213625.
64. K. Siau and Z. Shen, ‘Mobile healthcare informatics’, *Med. Inform. Internet Med.*, vol. 31, no. 2, pp. 89–99, Jan. 2006, doi: 10.1080/14639230500095651.