Analyzing Pain Detection for Renovation of the Medical Landscape

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Abstract

With the importance of continuously monitoring a patient's pain left unsolved, a new method of pain detection was explored. Especially given the doctor shortages in third-world countries and a lack of equipment for those doctors and the success behind using technology in medicine in places like Africa, quantitative pain detection has been becoming increasingly valuable. Systematic literature review was used to analyze the different methods of pain detection in 24 research studies. Between tracking biological markers such as sweat levels, brain waves and blood pressure and AI computer vision technology, numerous research studies were analyzed to determine which method would prove more effective in the clinical landscape. Statistical tests were run across all of the data, and a significant difference was found: AI pain detection (82.90% accuracy) outperformed biomarker pain detection (72.42% accuracy) by a value of 1.89 (P-value=0.0048). In light of this information, clinics are advised to look into implementing this cheap, efficient, and simple method of pain detection to replace the ineffective and obsolete subjective evaluation (53% accuracy) due to the importance of health care, especially pain detection.

Introduction

Using modern technology, innovators have developed numerous applications for artificial intelligence(AI). Specifically in the medical field, artificial intelligence has guided surgeries and mapped disease spreads internationally. One specific issue doctors faced, however, has been the continued use of old and outdated methods for pain detection. Pain detection served and continues to serve an integral role in numerous clinical processes, allowing doctors to address and diagnose chronic and surgery-related pain conditions. Most clinics currently still rely on subjective evaluations given by the doctor. A graphic to visualize and quantify different levels of pain usually guided the subjective pain evaluations (See Fig. 1). A one on a pain scale would portray, through description or through an example image, that the patient was in no pain. Conversely, a ten on a pain scale would mean the patient experienced extreme pain shown by contortions in the face and body (Kaiser Permanente). They aimed to more specifically determine how much pain the patient felt. If the patient matched the descriptions on the chart under high pain according to the doctor's observation, the doctor would assume the patient was in high pain. However, more times than not, the chart did not remove the ambiguity of pain evaluation the doctor faced due to the extremely subjective nature of the evaluation (WebMD). Sometimes the patient failed to properly show the pain they were in, and other times the doctor did not properly interpret the patient's pain in their facial expression and movements. Furthermore, doctors would have false senses of confidence when diagnosing pain, causing the doctor's conception of patient pain to outweigh the genuine amount of pain the patient experienced (Hadjistavropoulos et al., 1996). Misdiagnosis of chronic pain conditions that went untreated or were conversely treated unnecessarily consequently occurred as a result.

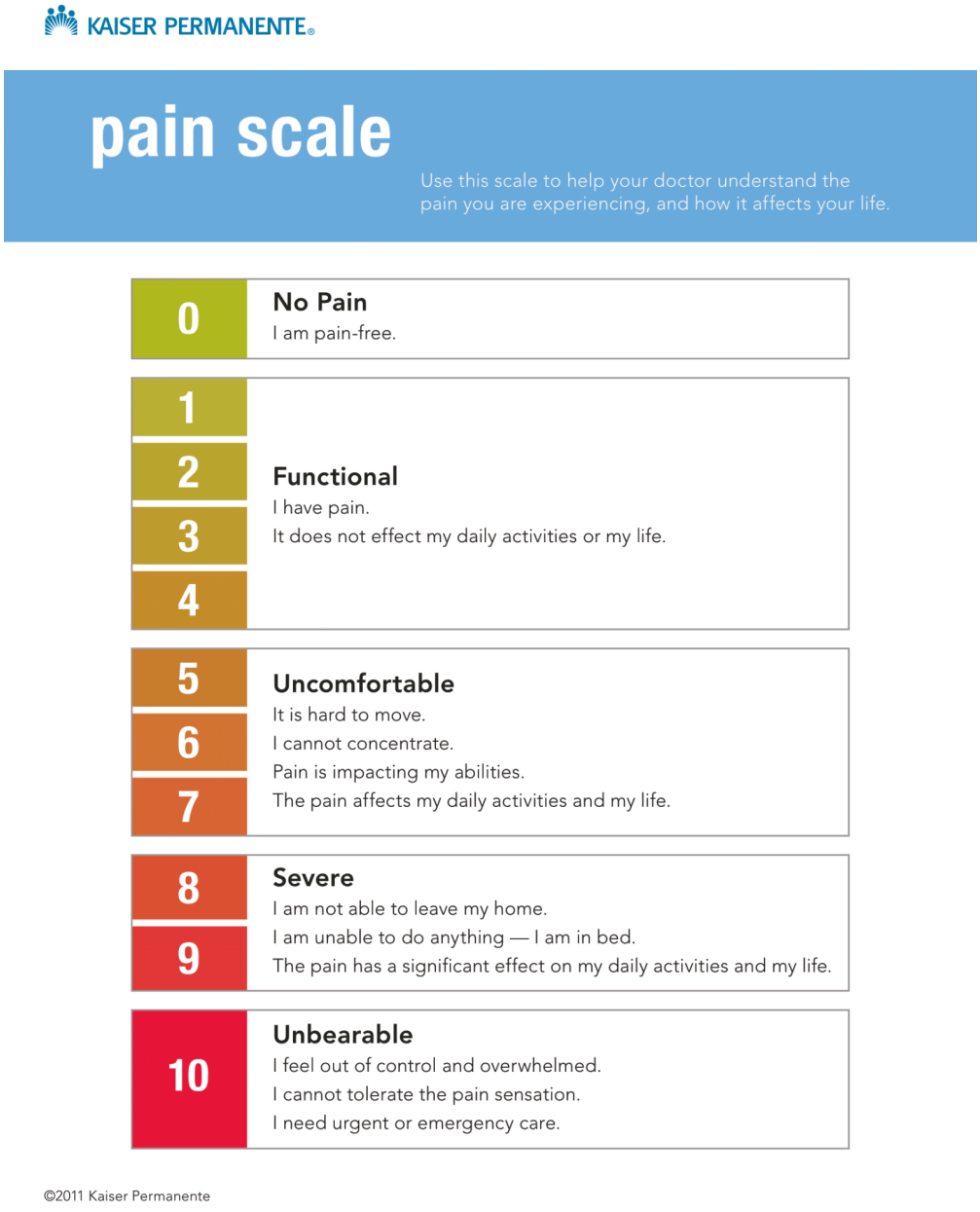


Figure 1: Displayed is an image of a typical pain scale seen in a clinical setting. This specific one dealt with chronic pain, but pain scales can also apply to immediate pain. These scales allowed doctors to attempt at deciphering the amount of pain patients have been or were experiencing.

With artificial intelligence, a more concrete evaluation of a patient's pain was made at little disadvantage. The assistance of a computer prevented doctors from incorrectly evaluating a patient's condition, especially under circumstances where the doctor cannot pay attention to the patient directly,

like during surgery. Essentially, an artificial intelligence algorithm will map out facial features of a patient based on position and shape. More algorithms were then used to translate the strength and position of these features into pain. While a majority of surgical procedures have been monitored by multiple medical staff who ensured the patient remains in stable condition, there was still the risk of human error. Even with robotically guided surgeries, these precarious settings still could make ample use of pain detection systems to immediately and accurately signal the presence of pain and alert the staff to attend to the issue in a timely manner (Sikka et al., 2015). However, it was still unknown whether or not computer vision machine learning systems are the optimal method of diagnosing pain.

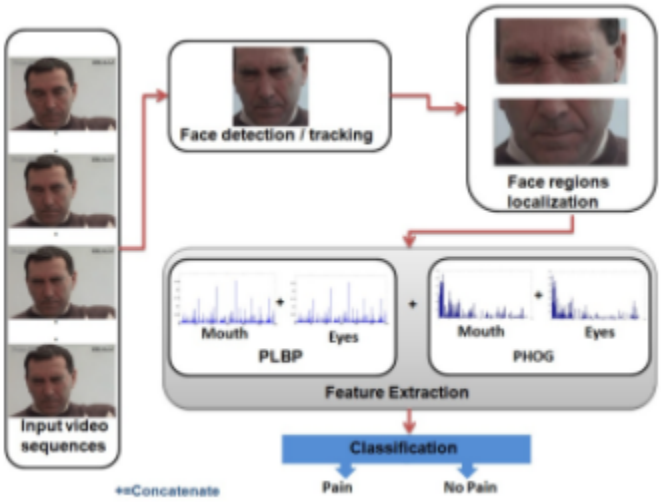


Figure 2: This figure shows the process with which the AI can detect facial contortions(Khan et al., 2013). It pinpoints different areas of the face and features on those areas and interprets their shape and position using an algorithm.

Another researched method involved tracking the patient's biological signals to accomplish the same task. In tracking pulse and blood pressure, doctors equipped the patient with a commonplace device like a sphygmomanometer, which consists of an inflatable cuff that measures the patient's blood pressure, and certain sphygmomanometers can also measure blood pressure (Drake University). Another common biological marker that allowed doctors to detect pain lied in epidermal activities. The most common

method involved monitoring epidermal activities, specifically those related to sweat. For this type of pain detection, an electrode on the skin monitored the conductivity of the surface through electrical currents. Since more sweat better conducts electricity, if the machine detected a current, it can be assumed that the patient was under stress that would translate to pain (Kong et al., 2020). The more stress caused by pain, the more current the system will detect.

Currently though, people have thoroughly researched the area of the medical industry concerning patient care. Pain detection first started as a subjective evaluation guided by pain scales, but at the turn of the century researchers developed technology. Research in this field analyzed the subjective observations guided by a pain chart (Lotsch and Ultsch, 2017). Subjective observation sometimes led to misinterpreted pain, and failed to provide a definitive answer in some situations where it could not be definitively determined if the patient was in pain or not (like in patients with dementia). Pioneers attempted the utilization of technology to replace the obsolete method. With the development of more advanced computing, computer scientists began to apply machine learning and artificial intelligence to many areas of the medical industry. This step immensely transformed the way people viewed medicine.

The new pain detection methods, specifically, were presented in multiple iterations and forms. Among these, most research divided the actual detection result into two forms: binary and non-binary. Binary pain detection simply detected if a patient was in pain or not (Sikka et al., 2015). Non-binary pain detection detected if a patient was in pain, and also how much pain they were in on a gradient, according to the DOL pain scale (Susam et al., 2018). Non-binary pain detection possessed the capabilities of its binary counterpart in addition to the ability to detect levels of pain, meaning the former was less precise and would narrow its range of applications. Luckily, both biological marker tracking and AI-aided facial recognition methods can perform non-binary pain detection.

Both biological marker tracking and artificial intelligence pain recognition consist of cheap components and are easy to construct and set up, so even the poorer communities like those in Africa

could implement them. One main problem in countries like Africa has been a lack of doctors, healthcare, and proper medical equipment. For every 1000 people in Africa, there are 2.3 healthcare workers, which is over 10 times less than the US's 24.8 healthcare workers per 1000 people (Pubmed, 2009). This deficiency sparked movements to implement remotely operated robot doctors during the COVID pandemic, and could also involve pain detection in the same manner in the future (World Economic Forum), stressing not only the convenience of pain detection systems, but also the importance to countries like Africa to produce and distribute such systems.

Research Question

"Are Artificial Intelligence systems or biological markers more effective in determining a patient's pain levels?"

Hypotheses

There could be one of three conclusions from researching the different methods of pain detection. One would support the use of AI systems over biological marker tracking. Another would support the opposite: the use of biological trackers over the use of AI systems. Alternatively, neither option could prove useful. This could mean that neither option has shown itself to be feasible, or another option trumps both of the aforementioned ones.

Methods of Previously Published Papers

Some researchers used machine learning algorithms to interpret the facial expressions of a patient largely, but other researched methods of determining the status of the patient exist, including: taking pulse, blood pressure, sweat levels, and monitoring chemical concentrations in the brain that serve as markers. For example, the higher concentration of certain brain chemicals implied that the patient had heightened pain on that interval of time. The machine learning method involved optimizing an algorithm and testing it through a database of multiple people with differing facial expressions of pain and other facial expressions without pain. This method was proven to have higher success rates of accuracy in predicting emotion when comparing the A.I. 's analysis of the actual emotion of the subject to the observer's evaluation (Surincelli et al., 2006). These practices drew upon feature extraction, where an algorithm tracked focal points and features of the face, as described by a table which determined what the features observed were, and could determine what expression the person displayed based on these features and their intensities (Werner et al., 2014). The biological method involved devices that monitor specific markers, such as a person's sweat levels or epidermal activity, which also produced very specific results with the right detected signal (Kong et al. and Kritikos et al., 2020, 2019). Researchers have not yet determined which of these two widely researched methods will serve better in clinical environments, however, as the only paper containing both methods does not compare the two directly.

Purpose and Gap in Research

The primary aim of this research paper involved comparing the two primary novel pain detection methods under the context of multipurpose clinical use, given the lack of research comparing pain detection systems. Pain detection remains important in both surgical and non-surgical situations, so that medical staff could properly and adequately administer required medicines or alter procedures in the case of surgery or other operations, in order to accommodate for patient pain (Gerlach and Kales, 2017). In the

past and even still in the present, the only method of detecting such pain was through subjective evaluation of the patient and doctor that did not actually give accurate interpretations of the pain experienced. There was plenty of experimental study found around both the computer vision and biological marker methods. In addition, studies exist that analyzed efficiencies of multiple experiments for each individual method, analyzing multiple biomarkers or in other cases analyzing multiple AI algorithms (Surcincelli et al., 2006). However, no published study compared different methods of pain detection as a whole to any concrete end. The need for new technology that accurately and effectively provides data on patient pain appeared critical for improving clinics and hospitals, which this research paper aimed to solve.

Scope

This paper compared multiple research studies to determine whether artificially intelligent vision systems or biological marker tracking would more effectively determine a patient's pain level, as well as each method's practicality, or if neither method performed better than the current doctor evaluation. It focused on the mechanism, time commitment, and effectiveness of machine learning compared to other biological signals like pulse, blood pressure and epidermal sweat readings.

Subjective observations of the doctor were included as well as biological markers and AI pain detection. Biological markers group pulse, blood pressure, and sweat activity into one category for data analysis. Chronic and injury pain data was retrieved from peer reviewed papers due to its clinical significance. Additionally, only patients during surgery, post-surgery, and in medical examinations were considered.

Methods

All research was gathered from various Science and Engineering journals and databases including IEEExplore and Science Direct. All of the source publications were from the past 25 years and discussed the evolution, efficiency, application, and practicality of the pain detection methods. The research of the papers reviewed takes place in research labs with proper equipment for conducting experiments, but research will take place online.

Quantitative data and qualitative data was collected from the different research papers being reviewed. Qualitative data showed how the given method detects pain and more specifically how this was accomplished. Quantitative data measured the success rates of the AI compared to other methods of evaluating facial expression from experiments, over the time it took to reach said success rate. Success was measured by the percentage success rate of a given system compared to how many factors it has to measure (amount of facial features or amount of biological signals) to give a result matching the presence or absence of pain, and to what degree. This project included subjective observations of the doctor for context, but data will not be accounted for in the literature review, as it is already evident the current method is unreliable. Additionally, only patients during surgery, post-surgery, and in medical examinations were considered.

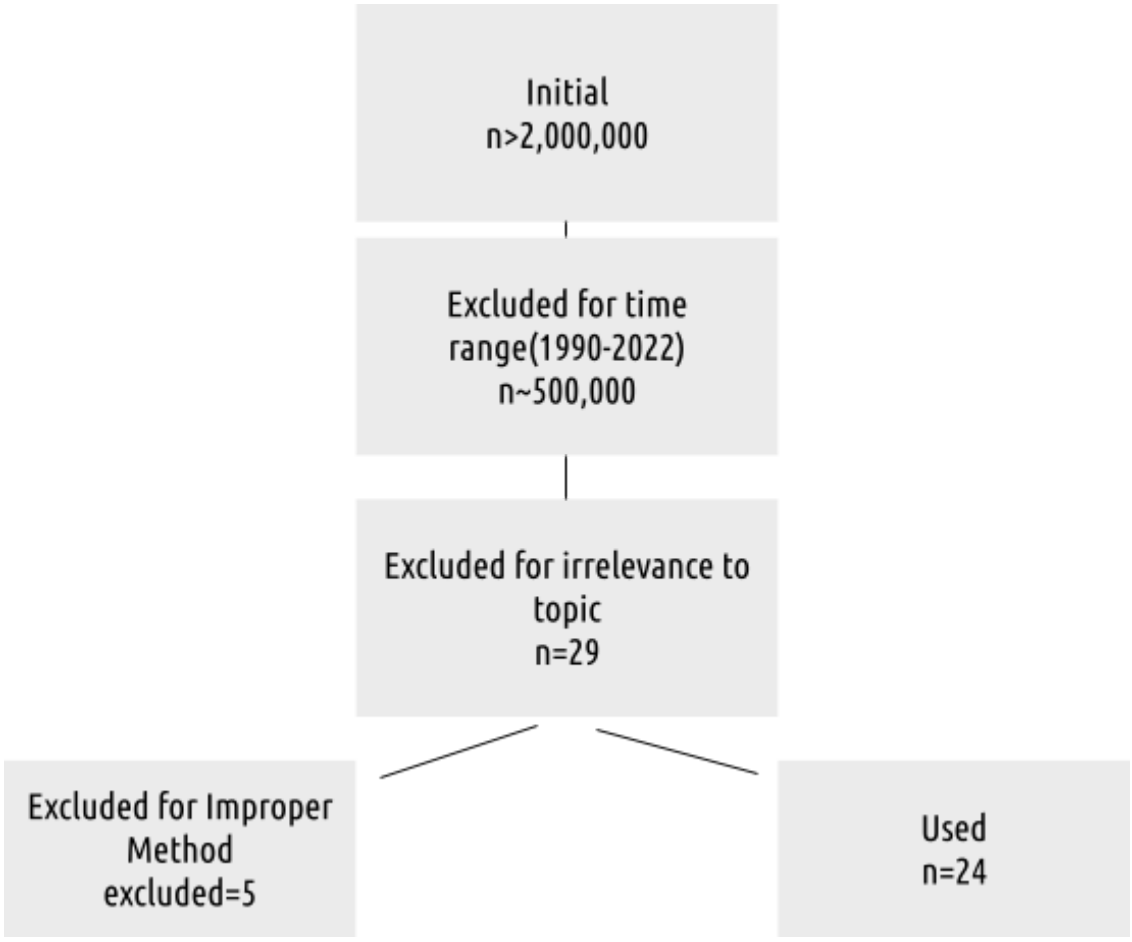


Fig. 3: The exclusion chart for this research study. Based on time range, relevant topic, and relevant method, papers were selected from multiple databases. This ensured useful and important data.

Through systematic literature review of experiments of various pain detection methods that tested biological signals and others that tested facial depression assisted by AI, literature review was conducted. Literature review cross-referenced the data from multiple research papers and experiments to analyze the data and establish conclusions from it, which was also done for this research project. This method of data interpretation intended to help doctors more easily the best method of keeping the patient stable, and to administer treatment depending on the amount of pain they experience based on results from multiple research studies. Performing such research experimentally or with a simulation would sacrifice too much accuracy during trials to work to the extent that this paper covers, especially within the provided time

frame. It would require too many trials under different conditions for multiple methods of pain detections to be feasible within a single research study. Therefore, systematic literature review best analyzed deficiencies in certain pain detection systems across multiple research studies regardless of the complexity of new technologies and specifics for each method of detection.

Pain detection showed significant potential to be implemented to prevent patients from being improperly cared for, and helped staff recognize if they are in pain or under stress in conditions where it would be difficult or impossible to determine so. Patients with Alzheimer's, autism, and other conditions that made it difficult for the doctor to effectively monitor patient pain no longer caused problems for the doctor. With the findings of this research, change can actually be made, and if the process is cheap enough, pain detection systems can be integrated on a larger scale to help people on a global scale.

Results

Raw data was gathered from around 20 papers, allowing trends to be analyzed between the samples of data (see Literature Review Table). According to the research studies examined, the current method of subjective evaluation had the lowest typical range of 35% to 79%, with the lowest average success rate of 55.7%. The sample of data for the biomarker pain detection and AI pain detection both had higher typical ranges than the subjective evaluation/pain chart method. The variance of AI pain detection was also roughly the same as biomarker pain detection, ranging from 65.4% to 97.7% (range of 32.3%) and from 58.4% to 90.4% (range of 32%), respectively. Given the current data, the average success rate of a biologically based pain detection system was 72.42%. The standard deviation of this dataset was ±12.1%, meaning it was unusual for the success rate to go below 60.32% or above 84.52%. For the AI method, the average success rate was 82.90%, and the standard deviation was ±9.87%. This means the success rate of this method typically stayed between 73.03% and 92.77%.

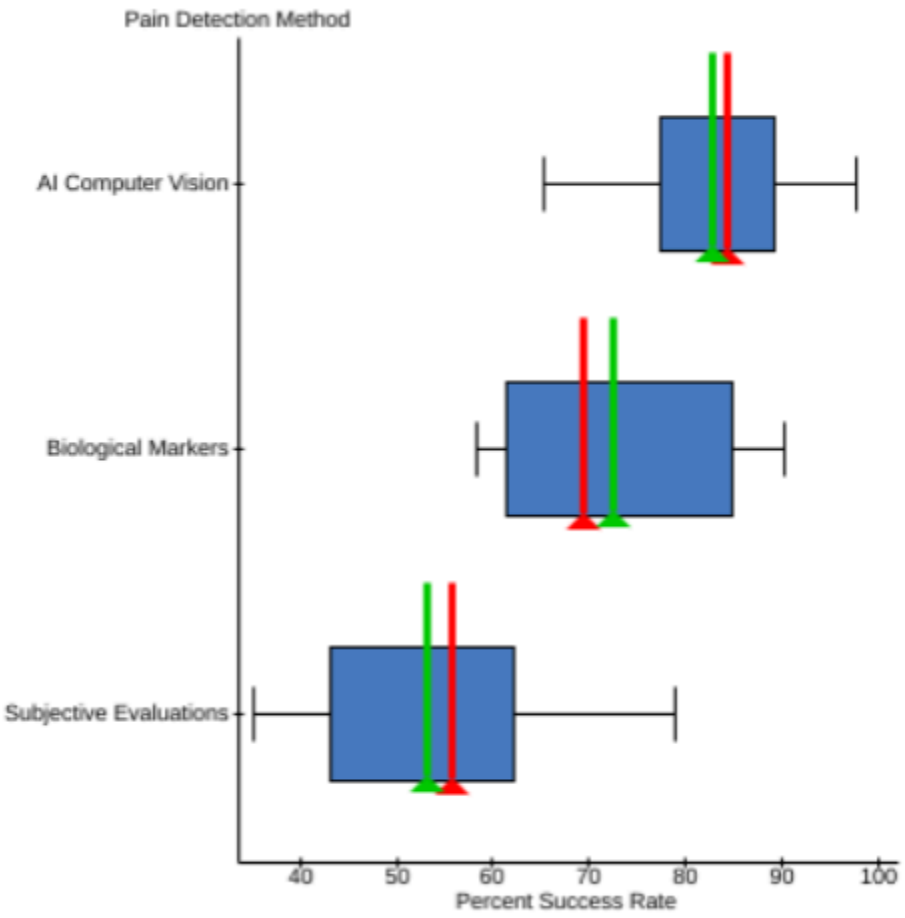


Figure 3: The following boxplot shows the distribution and shape of the efficiencies of each pain detection method. The central blue box illustrates the typical data range, and the bars on the ends of the box illustrate the other 50% of data that falls outside the typical range. This visual aid makes it easier to observe differences in performance between the observed methods.

Table 1: This table exists as a baseline for the two other methods. Should either of the proposed methods perform worse on average, this means the current method of subjective evaluations must remain in practice, which is not the case here. Therefore, there needs to be a new method of pain detection to replace this one.

Subjective Evaluations	Success rate
Coghill(2010)	62.0%
Coghill(2010)	56.0%
Hadjistavropoulos et al.(1996)	64.3%
Hadjistavropoulos et al.(1996)	36.0%
Hadjistavropoulos et al.(1996)	79.0%
Cook et al.(1999)	63.0%
Cook et al.(1999)	51.0%
Cook et al.(1999)	47.0%

Table 2: This table shows the overall success rates of different experimental research studies concerning biological pain detection through pulse, blood pressure, and epidermal activities(EDA). If, on average, the success rate of this method of pain detection proves better than other methods, it will be more viable.

Biological Markers	Success rate
Kong et al.(2020)	84.4%
Kong et al.(2020)	75.8%
Kong et al.(2020)	78.1%
Kong et al.(2020)	81.5%
Kong et al.(2020)	90.4%
Kong et al.(2020)	61.4%
Kong et al.(2020)	60.1%
Kong et al.(2021)	62.4%

Table 3: This table shows the overall success rates of different experimental research studies concerning the computer vision method. If, on average, the success rate of this method of pain detection proves better than other methods, it will be more viable then both current and alternative methods of pain detection.

AI Computer Vision	Success rate
Kharganian et al.(2016)	85.5%
Kelly(2001)	65.4%
J.B(2009)	81.4%
J.B(2009)	91.0%
Khan et al.(2013)	67.1%
Khan et al.(2013)	66.7%
Khan et al.(2013)	86.1%
Khan et al.(2013)	85.7%

Cook et al.(1999)	45.0%	Kong et al.(2021)	63.1%	Harms et al.(2010)	87.2%
Cook et al.(1999)	37.0%	Kong et al.(2021)	59.7%	Harms et al.(2010)	96.4%
Cook et al.(1999)	35.0%	Kong et al.(2021)	58.4%	Lötsch and Ultsch(2017)	83.3%
Cook et al.(1999)	64.7%	Kritikos et al.(2019)	60.1%	Lötsch and Ultsch(2017)	78.3%
Cowen et al.(2015)	45.6%	Kritikos et al.(2019)	62.0%	Lötsch and Ultsch(2017)	70.0%
Cowen et al.(2015)	41.1%	Kritikos et al.(2019)	61.9%	Menchetti et al.(2019)	76.7%
Cowen et al.(2015)	61.4%	Kritikos et al.(2019)	61.3%	Menchetti et al.(2019)	81.7%
Gerlach et al.(2017)	56.8%	Susam et al.(2018)	84.2%	Sikka et al.(2015)	88.8%
Gerlach et al.(2017)	61.5%	Susam et al.(2018)	85.3%	Surrincelli(2006)	90.0%
Rostrup(1999)	40.9%	Susam et al.(2018)	85.6%	Werner et al.(2014)	81.7%
Rostrup(1999)	62.2%	Susam et al.(2018)	85.6%	Werner et al.(2014)	97.2%
Rostrup(1999)	55.4%	Susam et al.(2018)	87.0%	Werner et al.(2014)	97.7%

Summary statistics

Table 4: The following table describes the data in plain numbers. The average values of data, their ranges, and minimum and maximum values can be observed to quantitatively and concretely showcase the difference in performance between the pain detection methods.

Method	Mean	Std. dev.	Median	Range	Min	Max	Q1	Q3
Subjective Evaluations	53.24 %	11.9%	55.7%	44.0%	35.0 %	79.0%	43.05 %	62.10%
Biological Markers	72.42 %	12.0%	69.45%	32.0%	58.4 %	90.4%	61.35 %	84.85%
AI Computer Vision	82.90 %	9.9%	84.40%	32.3%	65.4 %	97.7%	77.50 %	89.40%

Discussion

Upon analyzing the 24 research papers for data and additional supplemental research from other databases, artificial intelligence appeared to outperform biological markers in detecting patient pain. The biggest takeaway from the data, first and foremost, is the critical nature of changing the subjective evaluation system for pain detection. With success rates far below any of the novel methods, it offered no benefits; strictly issues in clinical practice. Especially given its importance in a lot of factors in patient care, it should be replaced. Additionally, doctor evaluation was highly inaccurate, even though the observer was highly confident of their evaluation (Hadjistavropoulos et al., 1996).

Many of the research papers focused on artificial intelligence and outlined its ease of use through systems that did not require attachment to the patient. In addition, complex enough algorithms could adequately adjust to mediocrely adverse environments. Mis-orientation of the vision device could be combated with depth perception incorporated into the AI algorithm, where the plane on which feature extraction changed to match the angle of the patient's face respective to the camera (Menchetti et al., 2019). However, it was not explicitly mentioned in the research on whether or not the system could adapt to different baseline neutrality. Patients with resting expressions that appeared to be in some degree of discomfort to the algorithm possessed the capability to hinder the performance of the vision system, although it is possible that the feature extraction algorithms could be improved to counteract this issue. The system's ability to map facial features and their strengths caused its specificity to increase by a large margin. In use, the AI algorithm translation can output a large amount of permutations for facial features into the pain scale, which makes its performance much better than the biological markers in terms of precision due to the numerous different iterations of pain feasibly quantified by the system.

Biological marker systems, while less accurate, displayed adverse use that AI systems fail under. For instance, in patients with high levels of cognitive impairment, the biomarker system still had an adequate success rate (O'Leary et al., 2015). These systems, such as the EDA system, required more equipment and also required attachment to the patient. This brought down their ease of use in clinical application, which in turn reduced their feasibility in surgical settings, especially if the surgery took place on or near the area where the system would need to be attached. Another problem with biological marker systems was their specificity. These systems applied a predetermined range of values to a pain scale for different purposes than the marker was intended to monitor. Although this did not inhibit the system's ability to interpret pain, it did interfere with its precision and therefore its accuracy as well.

While biological systems proved to have certain advantages over the AI vision systems, the AI still performed better with more capabilities. Precision, better raw success rate, and ease of use all surpass that of the biological marker system. While the biological marker system performed under more

circumstances due to its fixed position to the patient, this position led to the inability to perform in specific circumstances, primarily in surgery. Another factor that makes AI vision systems better is their ability to improve. Looking chronologically at research experimenting with this system, consecutive research has improved on a level unmatched by the biological counterpart. The vision system displayed capabilities improve not only by a large margin, but also in many more areas that biomarker systems can, such as in dealing with patient orientation relative to the camera, different baseline pain expressions, room lighting, and certain cognitive impairments.

Conclusion

From the data alone, it can be determined that on average, AI performed better than tracking biological markers to detect pain. The typical range, smaller standard deviation, and larger mean made the AI computer vision pain detection the better option. Across all of the research studies, the pain chart proved majorly suboptimal, so it very clearly serves no purpose, actually worsening the outcome for the patient in a lot of cases. Although the other two were close in performance, the data seemed to show that the monitoring of biomarkers like sweat and blood pressure for pain detection functioned significantly worse than the monitoring of pain through AI-aided vision systems, with a p-value of 0.0048. This value signified that there will be an observable, statistically significant difference between the performance of the vision system over the biological system 99.52% of the time, marking an extremely consistent outperformance of AI over the other considered methods, biological markers and subjective evaluations. A p-value this low signified the presence of sufficient evidence to confirm a difference in performance between the two methods. The actual pain detection systems did have respective faults, though. The biomarker system needed to be properly attached to function, and incorrect attachment to the body would read incorrect results, as mentioned. For the AI system, the patient needed to be in proper view of the camera in order for the system to function, which led to inaccuracies as well. However, despite these

inaccuracies, AI still performed better. In spite of this, AI pain detection is still advised to be employed due to its performance, continuous usability, and ease of use.

Limitations

Like many research studies, there were limitations with the present one. First off, the lack of variables prevented the results and conclusions from being as precise and detailed as they could have been. There was not enough, if any, data on much outside of the success rate of the pain detection models. Other limitations of the study included the scarcity of research studies on one particular clinical scenario or multiple and were overall very general.

Further Work

For the scope of this study, the success rate, the most critical variable, was examined. However, if the study were to be redone, more variables should have been considered, such as the prices of the devices and their maintenance costs or the time and setup required to use the devices. In addition to the consideration of other variables, further research could be done on various methods for each primary method of pain detection. Rather than examining the success of all of the biological markers as one, they could be examined as separate methods. In grouping them like done here, the data could have been skewed by the performance of one specific biological marker method. The same form of separation could also be done with the AI method, as researchers have used different forms of facial tracking and interpretation algorithms across different studies. In separating them, this could have been avoided, the optimal method of biomarker pain detection pinpointed and compared to the optimal form of AI pain

detection. These improvements could allow further studies to better understand the realm of pain detection technology and more precisely and in more detail determine the optimal system.

Acknowledgements

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Literature Review Table

Author(s) last names	**Title of paper**	**Year**		**Quantitative Data**	**Qualitative Data**		**Conclusion**
Coghill, Robert C.	Individual Differences in the Subjective Experience of Pain: New Insights into Mechanisms and Models	2010		Pain sensitivities of different types of people	Details on the differing pain reception of different people and steps to improve pain detection		Mainly covers the faults of pain scales because of the sensitivities of different people to pain that can differ from their actual pain.
Cook, Ailsa K., et al.	Assessing the Pain of People with Cognitive Impairment	1999		Success rates of trials where doctors tried to assess pain of the patients, with and without cognitive impairment.	Cases where patients were under- or mis-treated because of their disabilities		People with cognitive impairment do not normally express or feel pain and are under-assessed by the doctor way worse than already done with subjective evaluation of normal patients.

Ferrell, Bruce A.	Pain Management in Elderly People	1991		Amounts of medication for specific levels and types of pain Success in diagnosing pain Amount of people suffering from intolerable chronic pain	Types of medications for pain and for what pain it treats		Study focused less on the pain detection but more on how to treat the pain after it has been diagnosed. Also touches on the importance of pain detection and cases of chronic pain gone unreported.
Gerlach, L. B., & Kales, H. C.	Learning their language: The importance of detecting and managing pain in dementia	2017		none	Applicable situation for pain detection and use		This article covered a practical application of pain recognition in a rehab environment for patients with dementia that cannot express their pain. This shows the significance of pain recognition and potential use for the disabled or diseased.

Hadjistavropoulos, Heather D., et al.	Subjective Judgments of Deception in Pain Expression: Accuracy and Errors	1996		Data on the accuracy of the subjective evaluations Data on doctor confidence of their evaluation	Emphasizes the ineffective strategies for trying to determine patient pain		Outlined discrepancies in subjective pain detection, as well as showing data on its effectiveness. Doctor confidence was significantly higher than the actual accuracy of the evaluation.
Harms, M. B., Martin, A., & Wallace, G. L.	Facial emotion recognition in autism spectrum disorders	2010		Active brain parts for autistic people in pain	Literature review table		The project talked about how people recognize emotion, which could help with what the algorithm needs to look for especially for those with autism.
Hu1, X.-S., Nascimento1, T. D., Bender1, M. C., Hall3, T., Petty3, S., O'Malley3, S., Ellwood4, R. P., Kaciroti1, N.,	*Feasibility of a real-time clinical augmented reality and Artificial Intelligence Framework for pain detection*	n.d.		Accuracy for detecting pain based on patient Accuracy depending on method	Diagrams of how the experiments to detect pain live		The study analyzed a method of estimating brain activity using the AI method and was able to determine what side the pain was on.

Maslowski6, E., DaSilva1, A. F., 1Headache & Orofacial Pain Effort Lab, & DaSilva, C. A. A. F.	*and localization from the brain*.						
Kelly, A.-M.	The minimum clinically significant difference in visual analogue scale pain score does not differ with severity of pain.	2001		Not a lot(accuracy for a certain number of patients experiencing varying levels of pain)	Process of detecting multiple levels of pain		Explores the subjective evaluation of patient's pain to see if their evaluation matched the doctor's. Subjective evaluation can be altered by a lot of factors and human bias, and is not very effective. It is the current method though and is widely used.
Khan, R. A., Meyer, A., Konik, H., & Bouakaz, S.	Pain detection through shape and appearance features.	2013		Recognition rates for the 3 pyramid levels of pain detection	How feature extraction works(location,interpretation)		Tested different sets of facial features to detect pain as well as the possible shapes of those features. Describes the process of recognizing pain through video signals.

Kharghanian, R., Peiravi, A., & Moradi, F.	Pain detection from facial images using unsupervised feature learning approach	2016		Success of the method	Depictions(visual) of the feature-extraction method		Completely autonomous pain detection with computer vision-measures combinations of facial features and their strengths
Kritikos, J., Tzannetos, G., Zoitaki, C., Poulopoulou, S., & Koutsouris, D.	Anxiety detection from Electrodermal Activity Sensor with movement & interaction during Virtual Reality Simulation	2019		Success rate of the system and measurements of what levels of sweat concentrations are detected	How the EDA measures sweat levels and translates it to anxiety/pain		One possible pain detection method measuring skin activities
Kong, Y., Posada-Quintero, H. F., & Chon, K. H.	Pain detection using a smartphone in real time.	2020		Sweat level graphs at time intervals, and results for pain	Visual observation of pain detection system working		Seemingly promising method of detecting pain in people with EDA that measures sweat gland activities and pulse that can continuously measure pain. Can even be integrated into small devices like a smartphone to avoid clinical hassle. However, in

				detection/accuracy			the context of the article it is used more for outside the clinic but still has connections to the practices.
Kong, Y., Posada-Quintero, H. F., & Chon, K. H.	Sensitive Physiological Indices of Pain based on Differential Characteristics of ElectrodermalActivity	2021		Data on the readings of the EDA device and the success rate of pain detection for numerous trials			Used biomarkers(EDA) to measure pain with a large variance in success, using different methods of the EDA detection.
Lötsch, J., & Ultsch, A.	Machine learning in pain research.	2017		None	Systematic lit review table as well as their machine learning methods		Covers the uses of pain and machine learning and how it compares now and when it first started. Good for history and comparison. Also has some data to use

Lucey, P., Cohn, J. F., Matthews, I., Lucey, S., Sridharan, S., Howlett, J., & Prkachin, K. M.	Automatically detecting pain in video through Facial Action Units	2011		Head rotation to determine pain, graphs that show instances that the ai learns to start tracking pain	Figures on facial features that showcase pain, face shape mapping		This article highlights the clinical importance of pain detection. It also covers the most important facial features to observe and what features do what to form an expression of pain.
Menchetti, G., Chen, Z., Wilkie, D. J., Ansari, R., Yardimci, Y., & Cetin, A. E.	Pain Detection from Facial Videos Using Two-Stage Deep Learning	2019		Table of what values are expected for an expression of pain, accuracy. F1 score	Facial feature tracking and mapping		Two stage pain recognition yields high success rates in detecting pain presence and intensity, which closely matches the actual pain felt through mapping the face and continuously interpreting facial features
O'Leary, H. M., Marschik, P. B., Khwaja, O. S., Ho, E., Barnes, K. V., Clarkson, T. W.,	Detecting autonomic response to pain in Rett syndrome	2015		Data for EDA and HR(heart rate) used in pain	How the data was collected and the way the biomarkers were tracked		Specified study using biomarkers on patients with a certain inhibiting disorder to better quantify their pain.

Bruck, N. M., & Kaufmann, W. E.				detection trials Amounts of increase/decrease in both biomarkers			
Pederson, Henrick	Learning Appearance Features for Pain Detection Using the UNBC-McMaster Shoulder Pain Expression Archive Database	2015		Pain recognition performance and data on interpreted strength of the facial features	What kind of additions sacrifice accuracy for complexity in interpretation		Pain detection study using a database to test the method--specifically shoulder pain.
ROSTRUP, K. N. U. T. S. E. V. R. E.	Blood pressure and heart Rate responses to Cold Pressor test in patients admitted to hospital due to chest pain.	1999		Data on demographics for patients and their blood pressure and heart rate	none		Heart rate and blood pressure do show pain, or they are markers of it. heart conditions exaggerate this effects. They also show anxiety which can clue to pain. However, there is a lot of gray area and more

				with and without pain			research is needed to determine if it is a viable option for pain detection.
Schumacher, R., & Velden, M.	Anxiety, pain experience, and Pain report: A Signal-detection study.	1984		Sensitivity of patients to pain that could be measured	Doctors' observations of pain		Experiments were conducted to test the pain in patients and form trends with their anxiety. The two emotions are closely related, so detecting anxiety can help with solidifying the assessment that pain is present.
Sikka, K., Ahmed, A. A., Diaz, D., Goodwin, M. S., Craig, K. D., Bartlett, M. S., & Huang, J. S.	Automated Assessment of Children's postoperative pain using Computer Vision.	2015		Pain as dictated by machine vs human	Graphics on what characteristics denote pain, how the experiments were done		Covers the binary detection of pain(only yes/no, not in levels). Declares that measuring levels of pain is very difficult with current technology, especially in children. Children can not always express their pain so that provides necessity for this research.

Surcinelli, P., Codispoti, M., Montebarocci, O., Rossi, N., & Baldaro, B.	Facial emotion recognition in trait anxiety.	2006		Accuracy of detecting certain emotions with low and high anxiety	none		Facial recognition algorithms can extrapolate an emotion that someone is expressing from their facial expression, which works well, better under certain circumstances for certain people though
Susam, B. T., Akcakaya, M., Nezamfar, H., Diaz, D., Xu, X., de Sa, V. R., Craig, K. D., Huang, J. S., & Goodwin, M. S.	Automated Pain Assessment using Electrodermal Activity Data and Machine Learning	2018		Sensitivity and accuracy of the EDA method	Types of patients, methods of pain data interpretation		Using sweat levels to detect pain testing different ways of interpreting the biomarker's data to see which one provides the best results. Measured the specific level of pain-nonbinary
Werner, P., Al-Hamadi, A., Niese, R., Walter, S., Gruss, S., & Traue, H. C.	Automatic pain recognition from video and BIOMEDICAL SIGNALS.	2014		Accuracy tables compared with other methods	Facial tracking diagrams		Experiment on facial recognition to detect pain, as well as testing biomedical signals like brain signals. Quite informative but expensive equipment is needed and too much of a hassle to set up for simple checkups and even for surgery(might also be inconvenient for surgeries).

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