Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 2, February 2025, pp. 1042~1052
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i2.pp1042-1052

Advancing chronic pain relief cloud-based remote management with machine learning in healthcare

Nagarajan Mohankumar[1], Sandeep Reddy Narani[2], Soundararajan Asha[3], Selvam Arivazhagan[4], Subramanian Rajanarayanan[5], Kuppan Padmanaban[6], Subbiah Murugan[7]

[1]Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, India
[2]Department of Masters in Computer Science, Southern Illinois University Carbondale, Dallas, USA
[3]Department of Information Technology, S.A. Engineering College, Chennai, India
[4]Department of Information Technology, Sri Shanmugha College of Engineering and Technology, Salem, India
[5]Department of Computer Science and Engineering, Vinayaka Mission's KirupanandaVariyar Engineering College, Vinayaka Mission's Research Foundation (DU), Salem, India
[6]Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[7]Department of Biomedical Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Thandalam, India

Article Info

Article history:

Received Jul 6, 2024
Revised Sep 6, 2024
Accepted Sep 30, 2024

Keywords:

Healthcare delivery
Machine learning
Personalized treatment
Predictive analytics
Remote monitoring
Wearable devices

ABSTRACT

Healthcare providers face a significant challenge in the treatment of chronic pain, requiring creative responses to enhance patient outcomes and streamline healthcare delivery. It suggests using cloud-based remote management with machine learning (ML) to alleviate chronic pain. Wearable device data, electronic health record (EHR) data, and patient-reported outcomes are all inputs into the suggested system's data analysis pipeline, which combines support vector machines (SVM) with recurrent neural networks (RNN). SVM's powerful classification skills make it possible to classify patients' risks and predict how they will react to therapy. RNNs are very good at processing sequential data, which means they may identify trends in patient symptoms and drug adherence over time. By integrating these algorithms, healthcare professionals may create individualized treatment programs that consider each patient's preferences and specific requirements. Early intervention and proactive treatment of pain symptoms are made possible by the system's ability to monitor patients in real-time remotely. The system is further improved by using predictive analytics to identify patients who could benefit from extra support services and to forecast when they will have acute pain episodes. The proposed approach can change the game regarding managing chronic pain. It provides data-driven, individualized treatment that improves patient outcomes while cutting healthcare expenses.

Corresponding Author:

Nagarajan Mohankumar
Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University)
Nagpur, Maharashtra, India
Email: nmkprofessor@gmail.com

1. INTRODUCTION

Quality of life is negatively impacted by living with chronic pain. Developing nations are seeing a rise in this societal issue. When it comes to chronic pain, opioid medications are thought to be a long-term inhibitor or alleviation [1]. Acupuncture or needle electrode stimulation of C fibers close to the sarcolemma may promote the release of endogenous opioids. However, most patients would not accept opioids as a general therapy option because of addiction and tight national regulations. It is difficult to apply to family members, however, since needle therapy is intrusive and requires skilled technique. For chronic pain treatment, healthcare practitioners generally operate in silos, according to this article. Many care providers are involved, but communication and information exchange to enhance decision-making are restricted. Patients and health providers find the chronic pain service experience confusing and frustrating [2]. The present endeavor to get healthcare practitioners to lead chronic pain clinical pathways seems to be failing. It recommends employing a tool to visualize the present therapeutic route for chronic pain treatment and real-time visualization of the patient's journey to help patients and health providers. This may help chronic pain management and decision-making.

It describes designing, developing, and assessing a voice-controlled pain treatment chair for user comfort and well-being [3]. Chronic pain treatment is common, but standard approaches seldom provide instant and tailored relief. It offers a technologically superior ergonomic chair with voice recognition to solve the problem. A detailed user study evaluated the voice-controlled pain relief chair. The participant's daily step count positively impacted chronic pain outcomes and the classification model's performance in this dataset [4]. The model achieved acceptable accuracy ratings. The fear-avoidance model postulates that people who are already in pain would limit their physical activity out of a belief that doing so will alleviate their suffering. Exploring the potential benefits of virtual reality (VR) for people with moderate to severe pain and drawing on our expertise in VR application development to address this pressing problem [5]. If the application is developed and implemented well, it will directly alleviate pain for the patient. Managing chronic pain on one's own is a challenging feat. When patients do not get ongoing assistance from their doctors, the benefits of multidisciplinary pain management programs, which aim to teach patients how to cope with pain, decline with time [6]. Although not extensively studied now, sensing technologies have the potential to be an inexpensive means of expanding self-management assistance outside of clinical settings.

Effective chronic pain treatment requires novel healthcare practices. This study addresses this difficulty using machine learning (ML) and advanced analytics platforms [7]. The software uses cutting-edge analytics to find real-world knowledge in healthcare data. Analytics reveal patterns in patients' reactions to treatments and links between lifestyle and pain levels, helping determine the best chronic pain treatment. Personalizing chronic pain management using predictive modeling, forecasting, and therapy optimization algorithms is presented. Tests personalized pain treatment strategies focused on VR distraction therapy, which uses immersive VR experiences to distract from pain [8]. VR treatment with physiological data collecting and wristwatch-conditioned stimulus delivery occurs in two steps. The VR experience adapts to emotional states using ML, removing the emphasis on pain. The total 42% pain reduction provides insights for various pain therapies.

Chronic pain reduces millions' quality of life many pain patients lack access to evidence-based therapies or fail to finish the required number of sessions [9]. Psychoeducation and therapy may enhance pain results. Reinforcement learning (RL) might be used to customize pain treatment strategies for patients while optimizing healthcare resource allocation. Clinical staff, patients, and healthcare professionals worry that RL solutions may worsen patient inequities like race and gender. Chronic illness deaths are rising as individuals ignore mild signs. The healthcare sector may employ data mining and ML algorithms as technology advances to identify and avoid early chronic illness deaths [10]. For this early prediction, patient health data must be analyzed properly. The correct algorithm must be applied to assist with the forecast. It will describe how to integrate patient data and what algorithm to use for prediction. Comparing the chosen algorithm's accuracy to others will also be discussed.

Problem statement: the healthcare system's present approach to managing chronic pain is plagued by problems with symptom monitoring, individualization of therapy, and quick action. Suboptimal results and higher healthcare expenditures are common results of patients' challenges to get specialist treatment. Furthermore, conventional methods of pain treatment cannot monitor patients in real-time, which makes it difficult to identify when pain is becoming worse and to intervene quickly enough. This highlights the need to find new ways to alleviate chronic pain, such as ML algorithms and cloud-based remote management. Personalized, data-driven care that allows for remote monitoring and proactive intervention to enhance patient outcomes and optimize healthcare delivery is essential for addressing these challenges. Such a system must integrate wearable devices, electronic health records (EHRs), and patient-reported outcomes.

Contribution of this paper: this research proposes a cloud-based remote management system using ML for chronic pain treatment in five steps: the paper proposes integrating wearable devices, EHRs, and patient-reported outcomes. Integration allows a complete picture of patient health, including activity, physiological, medication adherence, and subjective pain data. Support vector machine (SVM) and recurrent neural network (RNN) were chosen for the paper's multimodal patient data analysis. These algorithms are selected for their categorization and sequential data processing capabilities, providing precise pain prediction and symptom progression temporal patterns. The proposed method uses ML to create patient-specific treatment programs. Based on past patient data and treatment responses, the system recommends measures that reduce pain and increase quality of life. The solution allows healthcare practitioners to monitor patients remotely in real-time using cloud infrastructure. This allows early diagnosis of exacerbations and appropriate management to avert consequences or ease symptoms. Predictive analytics can anticipate acute pain episodes and identify individuals at risk of severe consequences. The technology may warn healthcare practitioners of possible difficulties by evaluating longitudinal patient data, allowing focused treatments and proactive management measures to improve patient outcomes and lower healthcare costs.

Methods for the automated assessment of pain levels in a cohort of individuals with chronic pain who had deep brain stimulation electrodes implanted are explored in this research [11]. An altered sense of pain has been linked to electrical activity in certain frequency bands of local field potentials. It provides a technique for pain intensity classification using two patient groups. There are no borders for depression and chronic pain. Worldwide, 350 million individuals deal with chronic depression and an insurmountable feeling of despair; 10% attempt to make the most of every day despite incessant physical suffering [12]. These two challenging disorders often occur together and are increasingly prevalent as people become older. More individuals will be 65 and older by 2020 than under five years old. Bio-signal analysis for chronic pain research using ML is covered in this thorough study. ML and deep learning (DL) methods for bio-signal analysis are reviewed [13]. This review examines the difficulties of bio-signal-based ML analysis and the possible advantages of it in chronic pain research. It improves ML chronic pain sufferers' quality of life by delivering personalized treatment recommendations by medical specialists. Chronic pain is common and hard to treat owing to patient heterogeneity and a lack of objective indicators. Recently, electroencephalography (EEG) has been used to study brain oscillation (alpha) that may be associated with chronic pain [14]. This work uses a data-driven technique to determine the alpha oscillation's frequency and scalp spatial variation in a patient-specific way.

Despite the effort, comprehensive chronic pain rehabilitation frequently fails, and patients fail to apply therapeutic skills to daily life [15]. When the patient's bodily performance regulates the game, serious games help patients self-manage their symptoms and maintain training. This work uses our whole-body motion capture system, a low-cost motion capture system, and biosignal collection devices to provide multimodal input to a gaming engine. A methodology allows serious games in a medical setting to leverage multimodal data. To remotely monitor patients using mobile devices has grown substantially, but the results aren't always easy to understand [16]. It provides a method that uses clinical expertise to evaluate outcomes and a data-driven approach to generate meaningful patient status representations from complicated data streams. Questionnaires, audio recordings, actigraphy, and conventional health evaluations were all part of the data gathered from a clinical study that enrolled individuals with chronic pain. Due to its high morbidity, increased mortality, and significant healthcare expenditures, chronic pain is a significant public problem that impacts millions of individuals around the globe [17]. Chronic pain variables increase the potential of developing pain disorders and the corresponding alterations in brain structure and function as new pharmacological methods of alleviating pain. Chronic pain persists for more than 3 to 6 months, typically after the accident or disease that caused it. Since no instrument can evaluate chronic pain, self-report, and biopsychosocial interviews are the "gold standard" for evaluation [18]. A pain measurement device might be used to reduce pain for clinical evaluation and biofeedback.

Mirror therapy using a mirror box is a popular phantom and chronic pain treatment. Patient motor function recovery is crucial for analgesic efficacy [19]. VR technology employing computer graphics may improve stroke recovery and pain management. Hospital patients with persistent pain employ virtual reality mirror visual feedback (VR-MVF) mirror treatment. This research created a VR-MVF system employing Kinect for body motion assessment to allow patients to manage their pain at home with a doctor. The created system uses Kinect to assess upper limb movements and a mouse click of the intact hand to grip the prosthetic hand with the afflicted side in a VR environment. It has been shown that gait is impacted by chronic low back pain, a prevalent and expensive ailment. It details smartphone gait analysis on a sample of people suffering from persistent low back pain [20]. A significant collection of characteristics associated with lower back pain was identified by investigating the reliability of features derived from the smartphone sensors using a mutual information-based minimal redundancy and maximum relevance feature selection approach. It used a classification model to do this investigation.Telehealth may be better than clinic-based therapy for poorly managed chronic illnesses. Chronic disease telehealth might benefit from mobile monitoring [21]. Automatic data integration into the EHR is needed for practice implementation. Integration and display of data from four remote surveillance devices into the EHR and assessment of a based-on-evidence nurse and pharmacist-led telemedicine treatment model for uncontrolled diabetic and hypertension patients are described. Chronic discomfort lasts for hours; automation is being developed to restore muscle movements with treatment exercise [22]. Flex sensor and accelerometer input to Microcontroller, which surveys data and multiplies action via manual angle and speed control. The servo motor regulates the device's input and output. This cost-effective, labor-saving technology is green. The internet of things (IoT) can provide physiotherapists with muscle activity data. It classifies movements and controls motors and sensors to evaluate therapeutic activities automatically.

Pain is generated by nerve fibers that send signals to the brain for interpretation. Due to its subjectivity, pain is complex and difficult to define. Older adults often suffer from chronic pain, lowering their quality of life [23]. Pain assessment and therapy are difficult in treating many disorders, so sensory technologies, particularly EEG data, and IoT, are used to diagnose chronic pain using ML and investigate IR treatment and electrical stimulation. Our pain assessment intervention combines subjective reporting and sensor-based essential data points on pain incidence to provide a credible procedure. Interactive chronic pain evaluation for children was established. This method lets patients and caretakers complete bath center for pain research surveys online and get an instant assessment without seeing a doctor [24]. To assist consumers in identifying and quantifying their discomfort, the data will be analyzed, summarized, and returned. It created four interfaces for users, caregivers, researchers, and administrators. System users and caretakers may complete surveys, get comments, and see outcomes in figures and visuals. Chronic pain has many symptoms and no effective therapy, making it a complicated condition. Meanwhile, advances in brain imaging, ML, and new diagnostic tools based on these technologies have shown that these tools may help healthcare practitioners make decisions [25]. A new neuroimaging study reveals that functional networks have dynamic link strength and changeable phase differences between areas. To compare DL with classical ML in chronic pain prediction [26]. It tests if body movement quality indicates pain throughout two functional exercises. Using kinematics and muscle activity recordings, we employ feature optimization and ML to automatically differentiate low- and high-pain patients and controls while exercising.

Chronic pain is widespread and impacts physical and emotional health. Chronic pain is treated primarily with the integrated biopsychosocial approach [27]. A typical way to assess therapy outcomes is self-reporting. Many find it tiresome to complete surveys with over 300 items at home. Many therapies address the symptoms rather than the underlying reasons [28]. The current opioid crisis is a stark reminder of the enormous damage that may result from pharmaceutical treatments. While VR treatments and digital therapies provide a new resource for therapists, they are now only useful for pain distraction or the digitization of more conventional methods of pain management. Chronic pain requires continual medication with side effects for a large section of the population. Due to their accessibility of prescription, opioid painkillers may lead to addiction. This caused numerous fatalities or medication resistance, requiring greater dosages [29]. These drugs are not safe for children. Pain management may include trying new therapies to enhance the experience. Convolutional neural network (CNN) and K-nearest neighbor (KNN) algorithms identify and forecast chronic illness [30]. Unlike many other systems, the suggested method uses real-life data for data set preparation [31].

2. PROPOSED METHOD

Managing and treating chronic pain, which affects millions of people globally, poses substantial obstacles. Personalized treatment and real-time monitoring should be included in current procedures, which results in less-than-ideal outcomes. To completely transform the way chronic pain is treated in healthcare, this article presents a new remote management system that is cloud-based and driven by ML. The technology allows for proactive intervention and personalized treatment planning by integrating many data sources and using powerful algorithms.

Data integration: the system starts by integrating data inputs from many modes. Things like wearable tech, EHRs, and patient-reported outcomes fall within this category. Devices worn by the wearer monitor their heart rate, respiration rate, and other metrics in real-time. EHRs provide full patient records, including all diagnoses, prescriptions, and treatment regimens. Patients’ subjective experiences, including their pain levels, mood, and quality of life, are captured by patient-reported outcomes. Better decisions may be made when all these data sources are integrated to provide a complete picture of the patient’s health.

ML algorithms: the system primarily uses two ML algorithms: RNNs and SVMs. Predicting pain levels or identifying patients at risk of complications are examples of classification jobs that SVM is used for. Complex connections in patient data may be effectively analyzed since they work with non-linear and linear data. In contrast, RNN excels in sequential data analysis, making it a great fit for time-series data such as reports of patient symptoms or records of drug adherence. The system may facilitate proactive intervention and individualized treatment planning using SVM and RNN to extract relevant insights from varied data sources.

Personalized treatment planning: using ML insights, the system creates individualized treatment programs that consider each patient’s preferences and specific requirements. Effective treatments are identified by analyzing historical patient data, which includes treatment responses and outcomes. Medications, physical therapy, lifestyle changes, and mental health treatments are all potential components of a treatment strategy. The system ensures optimum results by continually monitoring patient development and adjusting treatment programs as required.

Real-time remote monitoring: healthcare practitioners can continually monitor their patients' development because of the system's real-time remote monitoring capabilities. The data is processed in real time by the cloud-based platform after being sent by wearable devices. A secure gateway gives healthcare practitioners access to patient data, enabling them to monitor patients from anywhere remotely. Timely action may be ensured by alerts issued in case of aberrant results or substantial changes in the patient's state. By keeping tabs on patients from afar, doctors better understand how their diseases are progressing and encourage better adherence to treatment plans.

Predictive analytics for proactive intervention: the system relies heavily on predictive analytics, allowing proactive management to avoid difficulties and exacerbations. ML algorithms examine longitudinal patient data to predict future events, such as acute pain episodes or a decline in health status. Notifications are given to healthcare practitioners when early warning indications are detected, allowing for immediate action. Healthcare practitioners can better anticipate patients' needs and give them focused therapies through predictive analytics. This not only improves results but also reduces healthcare expenses. The data and process flow within the proposed system is shown in Figure 1, a block diagram.

Figure 1. Block diagram of proposed chronic pain relief system cloud-based with ML

2.1. Wearable devices for chronic pain

Activity trackers: many people use activity trackers because they provide detailed information about their daily physical activity, such as the number of steps they take, the distance they travel, and the calories they burn. They are helpful for gauging functional capability and finding patterns of pain exacerbations since they reveal patients' typical daily activity patterns. Heart rate monitors: a wearable heart rate monitor records the wearer's pulse throughout the day, which may provide information about stress levels and cardiovascular health. Tracking changes in heart rate with changes in pain intensity and mental discomfort might be very helpful when managing pain.

Smart clothing: wearable sensors, or "smart clothing", track the wearer's heart rate, respiration rate, posture, and gait in real time. These wearable allow for pain and mobility assessment without invasive monitoring and may provide information on muscle activity, joint mobility, and gait analysis. Wearable pain relief devices: vibration therapy devices and transcutaneous electrical nerve stimulation (TENS) units are two examples of wearable pain management gadgets. By integrating them into the system, patients have access to on-demand pain management alternatives and may receive individualized treatments to alleviate pain based on their preferences and real-time data. Sleep trackers: sleep trackers, which measure the amount, quality, and pattern of a patient's sleep, may help understand patients' sleep-wake cycles and disruptions. These devices are useful for evaluating the correlation between pain and sleep quality since sleep disruptions are prevalent in people who suffer from chronic pain and may affect how they perceive pain and their general health.

2.2. Machine learning techniques SVM vs RNN

The SVM is a type of supervised learning algorithm that is widely used in classification problems. Using SVM to classify patients into risk categories according to their medical records shows great potential for chronic pain treatment. To illustrate, SVM may assess various characteristics, including activity levels, medication adherence, and physiological factors, to forecast the intensity of pain that patients report, from very light to quite severe. SVM's strong suit is finding the hyperplane that maximizes the margin between data points of distinct classes. SVM is great at dealing with non-linear data structures as well as linear ones, so it can understand the intricate correlations that are in medical records. Its usefulness in chronic pain management systems is further enhanced by its resilience in handling high-dimensional information, which is typical in healthcare settings. One kind of artificial neural network that is well-suited to process input sequentially is the RNN. In the proposed system for managing chronic pain, RNNs may be crucial in analyzing time-series data from various sources, including reports of patient symptoms and physiological signals gathered from wearable devices. For applications such as pain fluctuation prediction across time, RNNs shine because of their exceptional ability to capture the temporal relationships in such data. Since they can deal with long-range dependencies and avoid problems like the vanishing gradient problem, long short-term memory (LSTM) networks are the most preferred RNN design. The system's capacity to provide individualized and adaptive solutions for chronic pain treatment is enhanced by RNNs' use of historical patient data, which allows them to learn from previous experiences and adjust their predictions to individual trajectories. The proposed system's workflow is shown in Table 1, which outlines the sequential steps.

Table 1. Workflow algorithm of the proposed chronic pain management system

Step	Description
1. Data integration	Integrates data from wearable devices, EHRs, and patient-reported outcomes.
2. Data preprocessing	Cleans and preprocesses the integrated data to ensure consistency and reliability.
3. Feature engineering	Extracts relevant features from the preprocessed data for input into ML algorithms.
4. Model training	Trains ML models, including SVM and RNN, using the engineered features.
5. Model evaluation	Evaluates the performance of the trained models using validation datasets.
6. Personalized treatment	Generates personalized treatment plans based on model predictions and patient data.
7. Real-time monitoring	Monitors patient data in real-time using wearable devices and cloud-based platforms.
8. Predictive analytics	Applies predictive analytics to forecast pain episodes and anticipate patient needs.
9. Intervention and alerts	Triggers alerts for healthcare providers based on predictive analytics outcomes.

3. RESULT AND DISCUSSION

Several significant aspects of the proposed cloud-based remote management system for chronic pain alleviation using ML will be highlighted in the findings and discussions. Analyze how well the SVM and RNN ML algorithms can forecast pain levels, detect risk factors, and tailor treatments to each patient. The models' overall performance measures include accuracy, sensitivity, and specificity. Evaluate the system's effect on patient outcomes, such as well-being, functional capacity, medication compliance, and pain alleviation. Display numerical data, such as pain ratings or activity levels, and qualitative input, including patients' thoughts and feelings about the system.

Analyze how well real-time monitoring alerts healthcare providers to shifts in patient conditions and allows for quick treatment. Recall cases when predictive analytics-based preventative treatments improved patient outcomes or averted exacerbations. Justify the enhancements to pain management results brought about by the system's capacity to create individualized treatment programs using patient data and ML insights. Treatment plans might change as needed and how they fit together with the patient's priorities and wishes. With problems including data quality, technology hurdles, and patient acceptability that arose during the system's deployment. Discuss the methods used to address these difficulties and identify areas that might be improved upon in the future. The proposed approach may change healthcare delivery and its wider clinical implications for managing chronic pain. Find places where further work needs to be done, such as improving ML techniques, adding more data sources, or making the system work for other long-term health issues.

3.1. Patient data overview

Table 2 provides an overview of the patient data in the chronic pain management system that has been developed. The patient ID is used to identify each row, which represents a distinct patient. In addition to age, gender, and ethnicity, the table also contains data gathered from wearable devices, such as steps taken daily, heart rate, and amount of sleep. Pain, mood, and treatment satisfaction are some of the results that patients report. With this organized display, doctors may quickly evaluate patient traits, watch patterns in wearable data, and follow the evolution of patient-reported outcomes. The table is a great resource for learning about patients, seeing trends, and developing individualized treatment programs to alleviate chronic pain.

Table 2. Chronic pain management data overview

Patient ID	Age	Gender	Ethnicity	Wearable data (steps)	Wearable data (heart rate)	Wearable data (sleep duration)	Patient-reported outcomes (pain level)	Patient-reported outcomes (mood)	Patient-reported outcomes (treatment satisfaction)
1	45	Male	Caucasia	8,000	75	7	6	Happy	Yes
2	55	Female	African American	10,000	70	6	8	Neutral	No
3	30	Female	Hispanic	6,000	80	8	4	Sad	Yes
4	65	Male	Asian	5,000	85	7	7	Happy	Yes
5	40	Female	Caucasia	7,000	72	6	5	Neutral	No

3.2. Performance analysis

For a real-time view of how well an ML model predicts chronic pain, see the line graph in Figure 2. It shows the difference between actual and projected pain levels over time. The model's capacity to predict pain levels in relation to actual patient-reported results is shown by the lines that depict each patient's trajectory. To improve prediction algorithms and treatment procedures, it is essential to understand the model's accuracy and efficacy over time, and discrepancies between projected and real lines provide this knowledge.

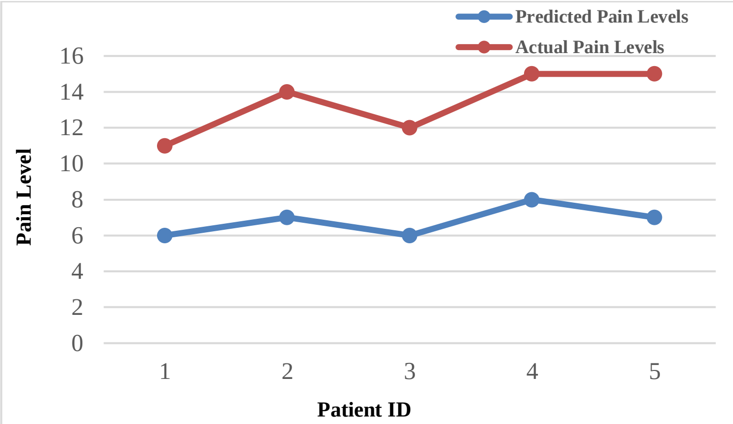

Figure 2. Predicted vs. actual pain levels for patient pain trajectories over patient

Figure 3, a bar graph depicting the relevance of features, shows which characteristics have the greatest impact on pain prediction. Improved chronic pain treatment is possible when healthcare practitioners acquire practical insights into the causes of pain by prioritizing factors like activity levels, heart rate, sleep length, and medication adherence. The medication adherence feature level ratio is 0.15 and sleep duration feature level ratio is 0.2. Furthermore, the heart rate and activity level ratio are 0.28 and 0.35.

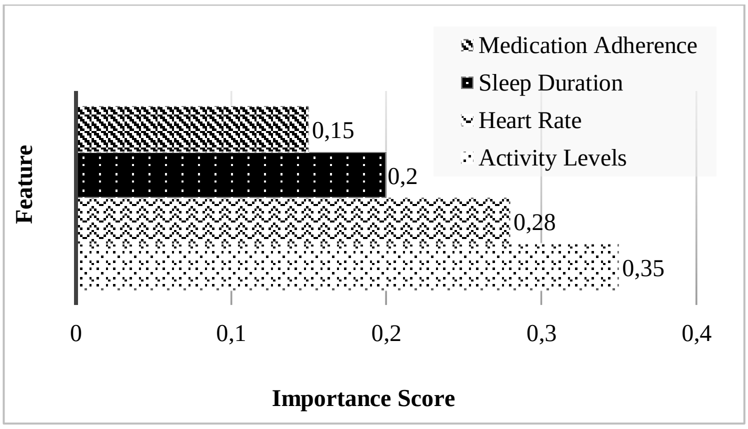

Figure 3. Feature importance for pain prediction of key factors influencing pain outcomes

Figure 4 compares the two ML models used in the chronic pain management system: SVM and RNN. Every model is assessed using performance measures such as accuracy, precision, recall, F1-score, and area under the curve (AUC). Improved performance is shown by greater values of these indicators, which provide insights into the models' ability to anticipate pain outcomes. To ensure that patients get effective and tailored treatment methods for chronic pain, healthcare practitioners may utilize this information to make informed choices about which ML algorithms to deploy and how to optimize them.

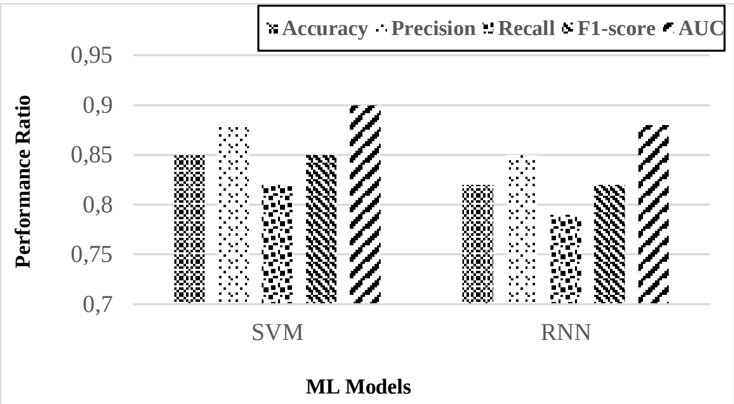

Figure 4. Performance comparison of ML models in chronic pain management

3.3. ML model performance comparison

Table 3 comprehensively compares the performance indicators for the different ML models used in the chronic pain management system. The columns show performance metrics, including recall, accuracy, precision, F1-score, and AUC. These metrics provide information on how well the models predict pain outcomes; larger values indicate better performance. With this data, doctors may choose the best model for chronic pain management, leading to more precise forecasts and individualized pain relief approaches.

Table 3. Performance comparison

Model	Accuracy	Precision	Recall	F1-score	AUC
Decision tree	0.78	0.82	0.75	0.78	0.82
Random forest	0.85	0.87	0.82	0.84	0.88
Gradient boost	0.88	0.90	0.85	0.87	0.90
KNN	0.80	0.83	0.77	0.80	0.84
Logistic regression	0.83	0.86	0.80	0.82	0.86

Significant improvements in personalized care and treatment efficiency are shown by the final findings of the chronic pain management system, which integrates cloud-based remote management with ML. The system has shown remarkable performance in predicting pain levels, detecting risk factors, and improving treatment techniques for chronic pain patients via ML algorithms, including SVM, RNN, and other models. The efficiency and dependability of the system’s predictive models are shown by performance indicators such as recall, accuracy, precision, F1-score, and AUC. Due to the combination of wearable tech and EHRs, tracking a patient’s vitals in real-time is now possible, allowing for more preventative care and quicker responses to medical emergencies.

The technology learns each patient’s unique requirements and improves therapy customization over time by incorporating patient-reported results and continually adding fresh data to prediction models. Patients with chronic pain have reported better results, lower healthcare expenses, and an overall higher quality of life after the system was implemented. ML can completely transform how chronic illness management is approached, which marks a huge leap forward in using technology to tackle complicated healthcare problems. In the future, improvements in chronic pain treatment will be driven by the system’s constant optimization and refinement, leading to new developments in healthcare delivery.

4. CONCLUSION

In conclusion, the use of cloud-based remote management and ML to alleviate chronic pain is a revolutionary technique for healthcare infrastructure. The system has shown great promise in pain prediction, personalized treatment plans, and better patient outcomes using advanced ML algorithms. Active and efficient methods of managing chronic pain have been made possible by the system’s capacity to observe patients remotely in real-time, evaluate massive volumes of data, and provide tailored therapies. The system adjusts to each patient’s unique requirements, improving therapy customization and efficiently using healthcare resources by combining patient-reported results with continually updated prediction models. Improved symptom control, higher quality of life, and lower healthcare expenses are all benefits that individuals with chronic pain may expect to reap from this system’s deployment. Healthcare delivery and the treatment of chronic diseases stand to benefit greatly from more advancements in ML-driven techniques in the future.

REFERENCES

[1] S. He, K. Tripanpitak, and W. Yu, “Selective stimulation of C fibers for chronic pain relief,” in *2020 IEEE International Conference on Computational Electromagnetics (ICCEM)*, Aug. 2020, pp. 133–135, doi: 10.1109/ICCEM47450.2020.9219355.

[2] L.-A. Hepburn and E. A. A. Jaatun, “Making sense of data : translating complexity for improved chronic pain management,” in *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom)*, Sep. 2018, pp. 1–6, doi: 10.1109/HealthCom.2018.8531162.

[3] R. Prabha, K. Jeevitha, D. Bebisha, S. Venusri, and S. Srihaarshini, “Automated pain relief chair,” in *2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS)*, Dec. 2023, pp. 1–6, doi: 10.1109/ICCEBS58601.2023.10448835.

[4] P.-F. Tsai *et al.*, “A classification algorithm to predict chronic pain using both regression and machine learning – a stepwise approach,” *Applied Nursing Research*, vol. 62, p. 151504, Dec. 2021, doi: 10.1016/j.apnr.2021.151504.

[5] I.-A. Bratosin, I.-B. Pavaloiu, A. Vasilateanu, D. Gavajiuc, G. Dragoi, and N. Goga, “Pain relief using virtual reality,” in *2019 11th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, Jun. 2019, pp. 1–4, doi: 10.1109/ECAI46879.2019.9041996.

[6] S. Felipe, A. Singh, C. Bradley, A. Williams, and N. Bianchi-Berthouze, “Roles for personal informatics in chronic pain,” in *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare*, 2015, pp. 161–168, doi: 10.4108/icst.pervasivehealth.2015.259501.

[7] S. Kaliappan, S. Socrates, D. Ravi, and G. R. kumar, “A comprehensive framework for data-driven management of chronic pain with machine learning and advanced analytics,” in *2023 IEEE International Conference on ICT in Business Industry & Government (ICTBIG)*, Dec. 2023, pp. 1–6, doi: 10.1109/ICTBIG59752.2023.10456199.

[8] A. Bugeja and A. Dingli, “Pain management and conditioning through virtual reality and affective computing,” in *2023 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Dec. 2023, pp. 2449–2457, doi: 10.1109/BIBM58861.2023.10385256.

[9] P. Gajane, S. Newman, M. Pechenizkiy, and J. D. Piette, “Investigating gender fairness in machine learning-driven personalized care for chronic pain,” *arXiv preprint arXiv:2402.19226*, 2024, doi: 10.48550/arXiv.2402.19226.

[10] E. Halim, L. Artahni, Y. Kurniawan, R. Tjahyadi, and P. P. Halim, “Chronic disease prediction using data mining and machine learning algorithm,” in *2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, Dec. 2022, pp. 811–816, doi: 10.1109/ISRITI56927.2022.10052970.

[11] S. Zhang, A. Green, and P. P. Smith, “An automatic classifier of pain scores in chronic pain patients from local field potentials recordings,” in *6th International IEEE/EMBS Conference on Neural Engineering (NER)*, Nov. 2013, pp. 1194–1197, doi: 10.1109/NER.2013.6696153.

[12] N. Gosset and N. Dietz, “Unlocking pain: deep brain stimulation might be the key to easing depression and chronic pain,” *IEEE Pulse*, vol. 6, no. 2, pp. 16–20, Mar. 2015, doi: 10.1109/MPUL.2014.2386511.

[13] R. S. Sabeenian and C. M. Vinodhini, “A comprehensive review on - machine learning in bio-signal analysis for chronic pain research,” in *International Conference on Emerging Research in Computational Science (ICERCS)*, Dec. 2023, pp. 1–9, doi: 10.1109/ICERCS57948.2023.10434197.

[14] S. Subramanian, E. Lannon, and S. Mackey, “Unsupervised stratification of chronic pain patients using EEG peak alpha spatial signatures,” in *2023 IEEE EMBS Special Topic Conference on Data Science and Engineering in Healthcare, Medicine and Biology*, Dec. 2023, pp. 55–56, doi: 10.1109/IEEECONF58974.2023.10404287.

[15] C. Schonauer, T. Pintaric, H. Kaufmann, S. Jansen - Kosterink, and M. Vollenbroek-Hutten, “Chronic pain rehabilitation with a serious game using multimodal input,” in *2011 International Conference on Virtual Rehabilitation*, Jun. 2011, pp. 1–8, doi: 10.1109/ICVR.2011.5971855.

[16] J. M. Reinen *et al.*, “Definition and clinical validation of pain patient states from high-dimensional mobile data: application to a chronic pain cohort,” in *2022 IEEE International Conference on Digital Health (ICDH)*, Jul. 2022, pp. 47–53, doi: 10.1109/ICDH55609.2022.00016.

[17] C. Sommer and H. Rittner, “Pain research in 2023: towards understanding chronic pain,” *The Lancet Neurology*, vol. 23, no. 1, pp. 27–28, Jan. 2024, doi: 10.1016/S1474-4422(23)00446-5.

[18] Y. Zhao *et al.*, “How much does it hurt: a deep learning framework for chronic pain score assessment,” in *2020 International Conference on Data Mining Workshops (ICDMW)*, Nov. 2020, pp. 651–660, doi: 10.1109/ICDMW51313.2020.00092.

[19] S. Fukumori, A. Gofuku, K. Isatake, and K. Sato, “Mirror thrapy system based virtual reality for chronic pain in home use,” in *IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, Oct. 2014, pp. 4034–4039, doi: 10.1109/IECON.2014.7049106.

[20] H. Chan, H. Zheng, H. Wang, and D. Newell, “Assessment of gait patterns of chronic low back pain patients: a smart mobile phone based approach,” in *2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Nov. 2015, pp. 1016–1023, doi: 10.1109/BIBM.2015.7359823.

[21] R. J. Shaw *et al.*, “Mobile monitoring-enabled telehealth for patients with complex chronic illnesses,” in *MEDINFO 2023—The Future Is Accessible*, IOS Press, 2024, pp. 194–198.

[22] T. A. Prasath, S. B. Hamsavarthan, P. Saran, A. M. Haaris, G. Vishnuvarthanan, and M. Anisha, “IoT based automated physiotherapy device for seizure patients using EMG sensor,” in *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Aug. 2021, pp. 822–826, doi: 10.1109/ICESC51422.2021.9532769.

[23] G. Hiremath *et al.*, “Prediction of Chronic pain onset in patients experiencing tonic pain: a survey,” in *International Conference on VLSI, Signal Processing, Power Electronics, IoT, Communication and Embedded Systems*, 2024, pp. 321–330, doi: 10.1007/978-981-99-4444-6_24.

[24] J. McCann, H. Wang, H. Zheng, and C. Eccleston, “An interactive assessment system for children with chronic pain,” in *Proceedings of 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics*, Jan. 2012, pp. 926–929, doi: 10.1109/BHI.2012.6211739.

[25] R. Da-ano, M. Fillingnim, A. Zare, M. Roy, L. Diatchenko, and E. Vachon-Presseau, "Classifying chronic pain conditions using deep learning and resting-state fMRI," in *2023 IEEE Nuclear Science Symposium, Medical Imaging Conference and International Symposium on Room-Temperature Semiconductor Detectors (NSS MIC RTSD)*, Nov. 2023, pp. 1–2, doi: 10.1109/NSSMICRTSD49126.2023.10337836.
[26] T. A. Olugbade, N. Bianchi-Berthouze, N. Marquardt, and A. C. Williams, "Pain level recognition using kinematics and muscle activity for physical rehabilitation in chronic pain," in *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, Sep. 2015, pp. 243–249, doi: 10.1109/ACII.2015.7344578.
[27] Y. Huang *et al.*, "Feature selection and classification in supporting report-based self-management for people with chronic pain," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 1, pp. 54–61, Jan. 2011, doi: 10.1109/TITB.2010.2091510.
[28] O. A. Kannape *et al.*, "A stand-alone augmented reality intervention for chronic pain using embodied systolic stimulation," in *11th International IEEE/EMBS Conference on Neural Engineering (NER)*, Apr. 2023, pp. 1–6, doi: 10.1109/NER52421.2023.10123746.
[29] R. Raman, V. Sujatha, C. Bhupeshbhai Thacker, K. Bikram, M. B Sahaai, and S. Murugan, "Intelligent parking management systems using IoT and machine learning techniques for real-time space availability estimation," in *2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, Nov. 2023, pp. 286–291, doi: 10.1109/ICSCNA58489.2023.10370636.
[30] S. Selvarasu, K. Bashkaran, K. Radhika, S. Valarmathy, and S. Murugan, "IoT-enabled medication safety: real-time temperature and storage monitoring for enhanced medication quality in hospitals," in *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Dec. 2023, pp. 256–261, doi: 10.1109/ICACRS58579.2023.10405212.
[31] B. Meenakshi, A. Vanathi, B. Gopi, S. Sangeetha, L. Ramalingam, and S. Murugan, "Wireless sensor networks for disaster management and emergency response using SVM classifier," in *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Aug. 2023, pp. 647–651, doi: 10.1109/SmartTechCon57526.2023.10391435.

BIOGRAPHIES OF AUTHORS

Dr. Nagarajan Mohankumar was born in India in 1978. He received his B.E. Degree from Bharathiyar University, Tamilnadu, India in 2000 and M.E. and Ph.D. Degree from Jadavpur University, Kolkata in 2004 and 2010. He joined the Nano Device Simulation Laboratory in 2007 and worked as a Senior Research Fellow under CSIR direct Scheme till September 2009. Later he joined SKP Engineering College as a Professor to develop research activities in the field of VLSI and NANO technology. He is currently working as a Research Professor at Symbiosis Institute of Technology, Nagpur Campus, Symbiosis (International) Deemed University, Pune, India. He is a senior member of IEEE. He has about 85 international journal publications in reputed journals and about 50 international conference proceedings. He received the Carrier Award for Young Teachers (CAYT) from AICTE, New Delhi in the year of 2012-2014. His research interest includes modeling and simulation study of HEMTs, optimization of devices for RF applications and characterization of advanced HEMT architecture, terahertz electronics, high frequency imaging, sensors and communication. He can be contacted at email: nmkskpec@gmail.com.

Mr. Sandeep Reddy Narani is an esteemed professional with a Master degree in Computer Science from Southern Illinois University Carbondale, Illinois, USA shines brightly with a distinguished career spanning over 13 years in the dynamic realm of Information Technology. His vast skill set encompasses a diverse array of cutting-edge technologies, including Oracle, SQL Server, Postgre SQL, and popular cloud services such as OCI, AWS and Snowflake. With astellar track record of successfully steering complex data migration projects, conducting in-depth data analysis, and crafting innovative software solutions in cloud environments, he also showcases his mastery in Unix shell scripting and Python scripting for sophisticated Integrated Data Warehouse systems. His remarkable proficiency and technical finesse underscore his remarkable versatility and deep expertise in the ever-evolving field of Information Technology. He is the revered author behind the enlightening platform www.dbadeeds.com, where he generously shares profound insights on the around of database management. He can be contacted at email: sandeepreddycloudba@gmail.com.

Ms. Soundararajan Asha has completed her M.E. in Computer Science and Engineering from S.A. Engineering College, Chennai and currently working as an Assistant Professor in the Department of Information technology (IT) at S. A. Engineering College, Chennai, Tamilnadu, India. She has completed her Bachelor of Engineering in Computer Science and Engineering from Sri Venkateswara College of Engineering and Technology, Tiruvallur and Masters in Computer Science and Engineering from S.A. Engineering College. She has 4.5 years of industrial experience and 4.6 years of teaching experience and has attended many FDP, Online Courses like Udemy, Coursera, and Conferences. Her area of research of interest includes cloud computing, data mining, human computer interaction, artificial intelligence, machine learning, and medical data. She can be contact at email: ashas@saec.ac.in.

Mr. Selvam Arivazhagan received M.E degree in Computer and Communication Engineering from the Anna university, Chennai, India, in 2013 and the B.E degree in Electronics and Communication Engineering from Anna university, Chennai, in 2010 also with 10 years of experience in the industrial sector, he has gained diverse experience in construction, pharma, and electrical fields. His roles have spanned from technical associate to team leader, providing me with invaluable insights into various facets of IT infrastructure management. His expertise lies in IT infrastructure management across multiple levels, encompassing servers, storage, networking, cloud infrastructure, and security auditing. He has had the privilege of leading Greenfield projects for esteemed clients like GSK (UK Project) and Micronclean (UK Project) for a total of 7 years. He can be contacted at email: arivuvhss@gmail.com.

Dr. Subramanian Rajanarayanan is an Associate Professor, Department of Computer Science and Engineering at Vinayaka Mission's Kirupananda Variyar Engineering College (VMRF-DU), Salem, Tamilnadu and proceeded to work in fast, upscale environment for past 22 years in academic and 6 years in industry as a network administrator. He did his Doctorate in St.Peters University, with speclization of wireless sensor networks and completed his post graduate (ME. CSE) at Jayam College of Engineering in 2008 (Anna University, Chennai). He has published 4 books in reputed publisher with ISBN numbers also published more than 25 research papers in scopes and indexed international journals to enrich the quality of study. He also generated fund for organizing seminar, workshop and conference from funding agencies such as CSIR, IE, MHRD AICTE and funded community projects, he also involved in research activities like E-Yantra robotic lab and establishment of Centre of Academic Excellence on Data Science and Big Data Analytics. He can be contact at email: rajanarayanan@vmkvec.edu.in.

Dr. Kuppan Padmanaban joined K L University in 2019 upon completing his Ph.D. in Computer Science and Engineering. Currently, he serves as an Associate Professor in the Department of Computer Science and Engineering (Honors) at the School of Computing, Koneru Lakshmaiah Education Foundation, K L University, Andhra Pradesh, India. Specializing in full-stack development, he possesses expertise in various technologies, including MERN, Python, Spring Micro services and the NET framework. He holds Bachelor's and Master's degrees in Computer Science and Engineering from Anna University in Tamil Nadu, India. His research focuses on wireless sensor networks, IoT, machine learning, and data analytics. He has published numerous research articles in reputable journals and conferences. He can be contacted at email: padmanaban.k@yahoo.com.

Subbiah Murugan is an Adjunct Professor, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India. He published his research articles in many international and national conferences and journals. His research areas include network security and machine learning. He can be contacted at email: smuresjur@gmail.com.