

A Proximity–Margin Hybrid Learning Architecture for IoT-Enabled Vibroarthrographic Signal Analysis in Knee Health Diagnostics

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ABSTRACT

Knee osteoarthritis (OA) and ligament injuries are among the most common musculoskeletal disorders affecting mobility and quality of life, particularly in aging populations. Early diagnosis and continuous monitoring are critical for effective treatment, but traditional diagnostic methods, such as X-rays and MRI, often detect abnormalities only at advanced stages, making early intervention challenging. These conventional techniques are also expensive, time-consuming, and require specialized facilities and expertise, which limits accessibility for regular monitoring. Vibroarthrography (VAG) has emerged as a non-invasive approach that records acoustic and vibrational signals generated by the knee joint during movement, providing valuable insights into joint health. However, interpreting VAG signals manually is difficult and prone to errors, and standalone clinical evaluation cannot capture the complexity of signal patterns effectively. This research addresses these limitations by integrating VAG with machine learning algorithms to classify knee conditions into three target classes: normal, osteoarthritis, and ligament injury. The system employs models such as Support Vector Machine classifier (SVM), K-Nearest Neighbours Classifier (KNN), Decision Tree Classifier (DTC), and a hybrid stacking model combining SVM and KNN also known as KneeSense FusionNet Model. The proposed system provides a user-friendly interface for clinicians and patients, enabling real-time, accurate assessment and continuous monitoring of knee health. Its significance lies in offering a cost-effective, non-invasive, and reliable diagnostic tool that facilitates early detection, personalized treatment, and improved patient outcomes, while overcoming the limitations of traditional diagnostic methods.

Keywords: Knee osteoarthritis, ligament injury, vibroarthrography, machine learning, stacking model, Musculoskeletal Disorders, Predictive Classification, Medical Diagnostics

1.INTRODUCTION

According to the World Health Organization (WHO), 528 million people worldwide suffer from degenerative joint diseases. Approximately 73% of those with osteoarthritis are individuals over the age of 55. With the aging of the global population, this number is expected to gradually increase [1]. All the synovial joints have a layer of articular cartilage, which enables smooth, painless and almost frictionless joint movement, properties that are highly affected during OA [2].

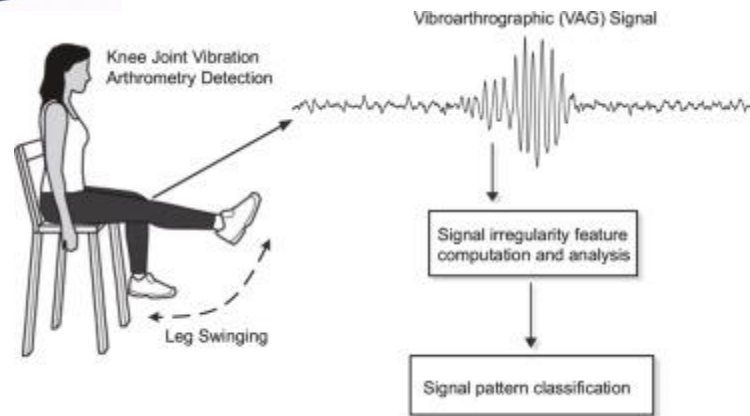


Figure 1: Quantification of knee vibroarthrographic signal irregularity.

Once the cartilage layer is compromised, the ongoing process of progressive damage is set in motion, and due to the limited cartilage regeneration capacity [3], progressive loss of motion, pain and stiffness of the affected joint develop. With the progression of osteoarthritis (OA), articular cartilage loses its mechanical properties, such as stiffness, strength, and elasticity as shown in figure 1. The Young's modulus decreases, and changes in the extracellular matrix led to a reduced ability to dissipate loads and increased cartilage permeability. The degeneration of the collagen network and loss of proteoglycans impair the cushioning function, while changes in the water content and friction coefficient accelerate joint damage [4]. These parameters can be monitored using diagnostic techniques such as MRI or vibroarthrography. Regardless of multiple treatment regimens, including nonsurgical modalities such as activity modification, physical therapy, pharmacological treatment and multiple surgical interventions, to date, OA is an incurable disease. At the end stage of OA, due to pain and restriction of motion, patients are qualified for total joint replacement (TJR). This treatment relieves pain; however, it restricts some daily activities, especially sports and in some areas also working abilities. Moreover, the survival rate of the TJR decreases every year after implantation, and a gross number of patients require revision arthroplasty due to, among others, aseptic loosening of the prosthesis. These findings are of great importance, especially for younger population [5].

2.LITERATURE SURVEY

Machrowska A et al. [6] focused on the diagnostic analysis of cartilage damage in the knee joint based on acoustic signals generated by the joint. They utilized a combination of advanced signal processing techniques, specifically empirical mode decomposition (EEMD) and detrended fluctuation analysis (DFA), alongside convolutional neural networks (CNNs) for classification and detection tasks. Acoustic signals, often reflecting the mechanical behavior of the joint during movement, serve as a non-invasive diagnostic tool for assessing the cartilage condition. EEMD is applied to decompose the signals into intrinsic mode functions (IMFs), which are then analyzed using DFA to quantify the scaling properties and detect irregularities indicative of cartilage damage. The separation of individual frequency components allows for multi-scale analysis of the signals, with each of the functions resulting from the analysis reflecting local variations in the amplitude and frequency over time and allowing for effective removal of noise present in the signal. Young F et al. [7] provided more readily deployable devices for use in any environment. Contemporary IMU-based gait assessment research has shown evidence of the robust quantifying of important clinical gait outcomes in, e.g., neurological disorders to gather more insightful habitual data in the home and community, given the relatively low cost and portability of IMUs. The aimed of this narrative review is to describe the ongoing research regarding the need to move gait assessment out of bespoke settings into habitual environments and to consider the

shortcomings and inefficiencies that are common within the field. Accordingly, broadly explore how the Internet of Things (IoT) could better enable routine gait assessment beyond bespoke settings.

Al-kahtani MS et al. [8] proposed Internet of Things (IoT) is an innovative technology with billions of sensors in various IoT applications. Important elements used in the IoT are sensors that collect data for desired analyses. The IoT and sensors are very important in smart cities, smart agriculture, smart education, healthcare systems, and other applications. The healthcare system uses the IoT to meet global health challenges, and the newest example is COVID-19. Demand has increased during COVID-19 for healthcare to reach patients remotely and digitally at their homes. The IoT properly monitors patients using an interconnected network to overcome the issues of healthcare services. The aim is to discuss different applications, technologies, and challenges related to the healthcare system. Jagatheesaperumal SK et al. [9] presented a framework that assesses an individual's existing health conditions, enabling people to evaluate their well-being conveniently without the need for a doctor's consultation. The framework includes a kit that measures various health indicators, such as body temperature, pulse rate, blood oxygen level, and body mass index (BMI), requiring minimal effort from nurses. To analyze the health parameters, they collected data from a diverse group of individuals aged 17–24, including both men and women. The dataset consists of pulse rate (BPM), blood oxygen level (SpO₂), BMI, and body temperature, obtained through an integrated Internet of Things (IoT) unit. La Mura M et al. [10] rise of the Internet of Things (IoT) has enabled the development of measurement systems dedicated to preventing health issues and monitoring conditions in smart homes and workplaces. IoT systems can support monitoring people doing computer-based work and avoid the insurgence of common musculoskeletal disorders related to the persistence of incorrect sitting postures during work hours. Their work proposed a low-cost IoT measurement system for monitoring the sitting posture symmetry and generating a visual alert to warn the worker when an asymmetric position is detected. Faisal AI et al. [11] utilized for continuous monitoring of joint movements during the normal daily activities of older adults and the healing process of joints (hips, knees or ankles) during the post-surgery period. A viable monitoring system can be developed by combining miniaturized, durable, low-cost and compact sensors with the advanced communication technologies and data processing techniques.

Matthew P et al. [12] provided a detailed overview of the Internet of Medical Things whilst discussing the design goals and challenges, the resource constraints and limitations of the complex healthcare systems. They also provided a detailed account of the research initiatives as well as off-the-shelf wireless motes, internet-enabled sensors and open-source platforms. A thorough account of the next-generation digital healthcare technologies and future research opportunities is provided. Abdulmalek S et al. [13] explored wireless- and wearable-sensor-based IoT monitoring systems and provides a classification of healthcare-monitoring sensors. also elaborate, in detail, on the challenges and open issues regarding healthcare security and privacy, and QoS. Finally, suggestions and recommendations for IoT healthcare applications are laid down at the end of the study along with future directions related to various recent technology trends. Athavale Y et al. [14] proposed a low-level signal encoding method which could improve data acquisition and storage in actigraphs, as well as enhance signal clarity for pattern classification. To further verify this study, they have used a machine learning approach which suggests that signal encoding also improves pattern recognition accuracy. Our experiments indicate that signal encoding at the source results in an increase in SNR (signal-to-noise ratio) by at least 50–90%, coupled with a bit rate reduction by 50–80%, and an overall space savings in the range of 68–92%, depending on the type of actigraph and application used in our study. Malesevic N et al. [15] presented results show that the angle measurement error falls within the reported values of the state-of-the-art IMU-based knee joint angle measurement devices while enabling a high-quality EMG recording over prolonged periods of time. While the device was designed and developed primarily for measuring knee

activity in individuals with CP, its usability extends beyond this specific use-case scenario, making it suitable for applications that involve human joint evaluation.

3. PROPOSED SYSTEM

The proposed system introduces an intelligent framework for real-time joint health assessment using IoT-integrated VAG (Vibroarthrography) signal features. It leverages a hybrid KneeSense FusionNet model, which combines the strengths of margin-based learning SVM and proximity-based learning KNN for accurate classification of knee conditions. The system performs data preprocessing, feature analysis, class balancing, and multi-model evaluation before deploying the optimized hybrid model for prediction. Integrated with a user-friendly GUI, the system enables efficient training, evaluation, and real-time prediction of knee health conditions, enhancing early diagnosis and decision-making as shown in figure 2.

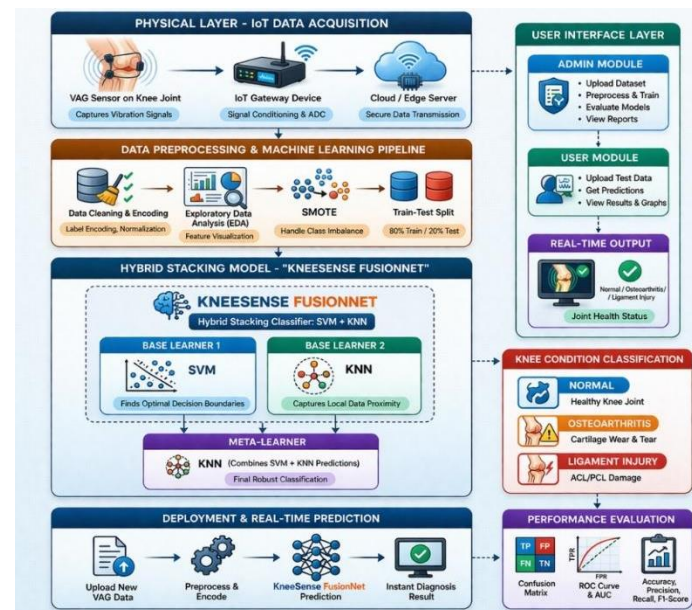


Figure 2: Proposed system architecture of VAG signal analysis

1. Data Acquisition and Loading: The system begins with the collection of VAG signal-derived datasets, which are uploaded through the graphical user interface. These datasets consist of various signal features such as RMS amplitude, peak frequency, spectral entropy, and zero-crossing rate. The uploaded data is validated and displayed to provide an initial understanding of the input structure before processing.

2. Data Preprocessing and Encoding: In this stage, the dataset undergoes cleaning by removing missing or inconsistent values to ensure data quality. Categorical features and the target variable (knee condition) are transformed into numerical form using label encoding techniques. The preprocessing ensures that the data is structured and compatible for training the KneeSense FusionNet model.

3. Exploratory Data Analysis (EDA): The system performs detailed exploratory analysis to understand feature distributions and relationships. Visualizations such as count plots, boxplots, violin plots, scatter plots, and correlation heatmaps are generated. These insights help in identifying key patterns and feature importance that influence the performance of the KneeSense FusionNet model.

4. Dataset Splitting and Balancing: The processed dataset is divided into training and testing subsets to evaluate model performance effectively. To address class imbalance issues, the SMOTE technique

is applied to generate synthetic samples for minority classes. This balanced dataset improves the generalization capability of the KneeSense FusionNet model.

5. Model Training using KneeSense FusionNet: The core of the system is the KneeSense FusionNet, a hybrid stacking classifier that integrates SVM as the base learner and KNN as the meta-learner. The model learns both optimal decision boundaries and proximity-based relationships among data points. This combination enhances classification accuracy and robustness for joint health prediction.

6. Model Evaluation and Performance Analysis: After training, the KneeSense FusionNet model is evaluated using multiple performance metrics such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices and ROC curves are generated to provide a detailed understanding of classification performance across different knee conditions.

7. Prediction and User Interaction: In the final stage, users can upload new test data through the interface, which is pre-processed using previously saved encoders. The trained KneeSense FusionNet model then predicts the knee condition for each input sample. The results are displayed in an interpretable format, enabling real-time joint health assessment and decision support.

4. RESULTS ANALYSIS

The results demonstrate the effectiveness of the proposed KneeSense FusionNet model in accurately classifying knee conditions using VAG signal features. Comparative analysis shows that the hybrid model outperforms individual classifiers such as SVM, KNN, and Decision Tree in terms of accuracy, precision, recall, and F1-score. The confusion matrices and ROC curves indicate improved classification performance and better discrimination between normal, osteoarthritis, and ligament injury classes. The integration of SMOTE and feature analysis further enhances model robustness by addressing class imbalance. Additionally, the user-friendly GUI enables real-time prediction and visualization of results.

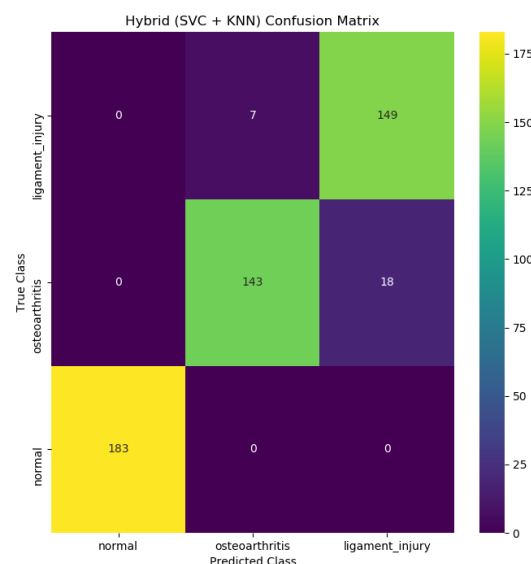


Figure 3: Confusion matrices obtained using KneeSense FusionNet Models.

The figure 3 presents the confusion matrix of the hybrid SVC + KNN model for classifying knee conditions. It shows that the model correctly identifies a high number of normal cases, with all samples accurately classified. Osteoarthritis cases are also largely predicted correctly, with only a small number misclassified as ligament injury. However, ligament injury cases exhibit significant misclassification, with most samples incorrectly predicted as osteoarthritis. The matrix highlights strong performance in

detecting normal and osteoarthritis conditions but comparatively weaker performance in identifying ligament injuries. The model demonstrates high accuracy with some limitations in class separation for ligament injury cases.

The figure 4 illustrates the AUC-ROC curves for the hybrid KneeSense FusionNet model using a one-vs-rest approach for three classes. The model achieves an AUC of 1.00 for the normal class, indicating perfect classification performance. For osteoarthritis and ligament injury, the AUC values are 0.97 and 0.98 respectively, demonstrating very high predictive capability. The curves remain close to the top-left corner, reflecting strong sensitivity and specificity across all classes. Compared to the random classifier baseline, the model shows significantly superior discrimination ability. The results confirm the robustness and reliability of the proposed model in distinguishing between different knee conditions.

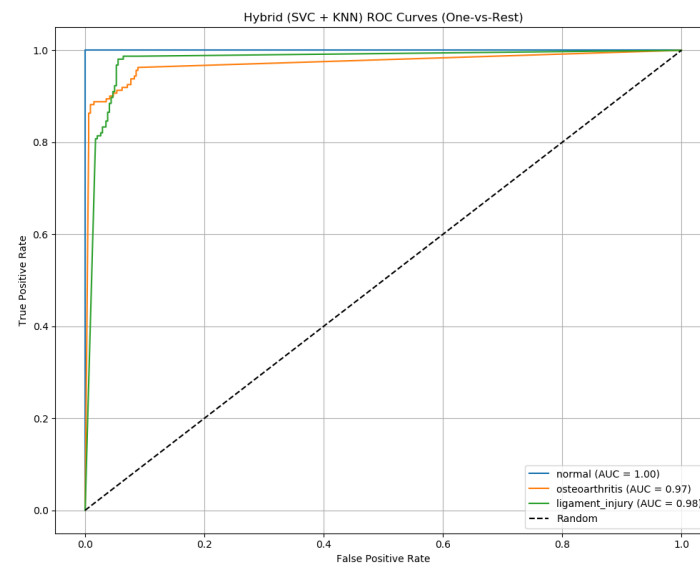


Figure 4: AUC-ROC Curves obtained using KneeSense FusionNet Models.

Prediction Completed!

Showing first 5 rows of test data with predictions:

	severity_level	treatment_advised	rms_amplitude	peak_frequency	spectral_entropy	zero_crossing_rate	mean_frequency	Knee_Condition_
Classified_As								
0	2	0	1.051421	20	-1799.219746	0.001	39.864485	normal
1	2	0	1.071817	20	-2010.827330	0.000	40.652874	normal
2	0	1	1.098748	20	-2172.177329	0.000	39.961072	osteoarthritis
3	3	2	1.063046	20	-1915.991388	0.000	39.860160	osteoarthritis
4	0	1	1.096699	20	-2156.652540	0.000	40.812210	osteoarthritis

Figure 5: Illustration of GUI interface displaying predictions on test data.

Figure 5 displays a table showing the first five rows of test data with predictions for the IoT-integrated VAG signal analysis system. It includes columns for classified severity levels (0 to 4), treatment advised (0 or 1), RMS amplitude, peak frequency, spectral entropy, zero-crossing rate, mean frequency, and the predicted knee condition. The data entries, such as severity level 0 with an RMS amplitude of 1.051421 and a predicted condition of “normal,” or severity level 2 with an RMS amplitude of 1.085748 and a predicted condition of “osteoarthritis,” provide specific insights into the joint health assessment.

Comparative Analysis

The performance comparison table 1 shows that the KneeSense FusionNet model outperforms all other models, achieving an accuracy of 95%, with precision, recall, and F1-score all above 94%, indicating excellent balance between correctly identifying positive cases and minimizing false predictions. The KNN Classifier performs well with 88.8% accuracy and consistent precision and recall, making it a reliable standalone model.

Table 1: Performance comparison of algorithms (a) Existing SVC. (b) Existing KNN (c) Existing DTC (d) Proposed KneeSense FusionNet Models.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KneeSense FusionNet	95.0	94.85	94.78	94.74
KNN Classifier	88.8	88.67	88.15	88.14
SVM Model	81.8	80.86	80.86	80.86
Decision Tree	68.8	50.26	66.67	55.79

The SVM model has moderate performance, achieving 81.8% accuracy and roughly equal precision, recall, and F1-score, showing it is effective but less robust than the hybrid approach. The Decision Tree model performs the weakest, with 68.8% accuracy and low precision (50.26%), suggesting it misclassifies a significant number of samples, although its recall of 66.67% indicates it still captures a portion of the true positive cases. Combining SVC and KNN in a stacking ensemble significantly improves predictive performance by leveraging the strengths of both classifiers, resulting in the highest accuracy, precision, recall, and F1-score.

5. CONCLUSION

The IoT-Integrated VAG Signal Analysis system successfully demonstrates the feasibility and effectiveness of using machine learning models for real-time knee joint health assessment. By integrating dataset preprocessing, exploratory data analysis, model training, and performance evaluation within a user-friendly GUI, the system enables both administrators and end-users to manage data and obtain accurate predictions efficiently. Among the models tested, the Hybrid KneeSense FusionNet model achieved the highest performance, indicating that combining classifiers can significantly enhance predictive accuracy and robustness. This research validates the potential of combining IoT-based signal acquisition with intelligent algorithms to support clinical decision-making, reduce diagnostic errors, and provide timely feedback for patients with knee conditions. The system presents a practical and scalable approach for automated joint health monitoring using VAG signals.

REFERENCES

- [1] Krakowski, P.; Rejniak, A.; Sobczyk, J.; Karpiński, R. Cartilage Integrity: A Review of Mechanical and Frictional Properties and Repair Approaches in Osteoarthritis. *Healthcare* 2024, 12, 1648.
- [2] Link, J.M.; Salinas, E.Y.; Hu, J.C.; Athanasiou, K.A. The Tribology of Cartilage: Mechanisms, Experimental Techniques, and Relevance to Translational Tissue Engineering. *Clin. Biomech.* 2020, 79, 104880.

- [3] Moore, A.C.; Burris, D.L. Tribological and Material Properties for Cartilage of and throughout the Bovine Stifle: Support for the Altered Joint Kinematics Hypothesis of Osteoarthritis. *Osteoarthr. Cartil.* 2015, 23, 161–169.
- [4] Grushko, G.; Schneiderman, R.; Maroudas, A. Some Biochemical and Biophysical Parameters for the Study of the Pathogenesis of Osteoarthritis: A Comparison Between the Processes of Ageing and Degeneration in Human Hip Cartilage. *Connect. Tissue Res.* 1989, 19, 149–176.
- [5] Purmani, S. S. R. (2025). Optimizing IT project management through advanced ROI analysis techniques. *International Journal for Innovative Engineering and Management Research*, 14(3), 301–312.
- [6] Machrowska A, Karpiński R, Maciejewski M, Jonak J, Krakowski P, Syta A. Multi-Scale Analysis of Knee Joint Acoustic Signals for Cartilage Degeneration Assessment. *Sensors*. 2025; 25(3):706. <https://doi.org/10.3390/s25030706>
- [7] Young F, Mason R, Morris RE, Stuart S, Godfrey A. IoT-Enabled Gait Assessment: The Next Step for Habitual Monitoring. *Sensors*. 2023; 23(8):4100. <https://doi.org/10.3390/s23084100>
- [8] Al-kahtani MS, Khan F, Taekeun W. Application of Internet of Things and Sensors in Healthcare. *Sensors*. 2022; 22(15):5738. <https://doi.org/10.3390/s22155738>
- [9] Jagatheesaperumal SK, Rajkumar S, Suresh JV, Gumaei AH, Alhakbani N, Uddin MZ, Hassan MM. An IoT-Based Framework for Personalized Health Assessment and Recommendations Using Machine Learning. *Mathematics*. 2023; 11(12):2758. <https://doi.org/10.3390/math11122758>
- [10] La Mura M, De Gregorio M, Lamberti P, Tucci V. IoT System for Real-Time Posture Asymmetry Detection. *Sensors*. 2023; 23(10):4830. <https://doi.org/10.3390/s23104830>
- [11] Faisal AI, Majumder S, Mondal T, Cowan D, Naseh S, Deen MJ. Monitoring Methods of Human Body Joints: State-of-the-Art and Research Challenges. *Sensors*. 2019; 19(11):2629. <https://doi.org/10.3390/s19112629>
- [12] Matthew P, Mchale S, Deng X, Nakhla G, Trovati M, Nnamoko N, Pereira E, Zhang H, Raza M. A Review of the State of the Art for the Internet of Medical Things. *Sci*. 2025; 7(2):36. <https://doi.org/10.3390/sci7020036>
- [13] Abdulmalek S, Nasir A, Jabbar WA, Almuahaya MAM, Bairagi AK, Khan MA-M, Kee S-H. IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. *Healthcare*. 2022; 10(10):1993. <https://doi.org/10.3390/healthcare10101993>
- [14] Athavale Y, Krishnan S. A Device-Independent Efficient Actigraphy Signal-Encoding System for Applications in Monitoring Daily Human Activities and Health. *Sensors*. 2018; 18(9):2966. <https://doi.org/10.3390/s18092966>
- [15] Malesevic N, Svensson I, Häggglund G, Antfolk C. An Integrated Approach for Real-Time Monitoring of Knee Dynamics with IMUs and Multichannel EMG. *Sensors*. 2023; 23(21):8955. <https://doi.org/10.3390/s23218955>