Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 31s (2025)
https://www.jneonatalsurg.com

High-Dimensional Block Feature Extraction and Deep Recurrent Multilayer Classification for Knee Injury Detection

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Cite this paper as: V. Sowmiya, Dr. V.S Lavanya, (2025) High-Dimensional Block Feature Extraction and Deep Recurrent Multilayer Classification for Knee Injury Detection, *Journal of Neonatal Surgery*, 14 (31s), 893-904

ABSTRACT

Knee injury exposure involves the specification for the estimation of abnormalities, damages irregularities within the knee joint and surrounding structures. In this process is critical for diagnosing various conditions, such as ligament injuries, cartilage damage and other soft tissue injuries. The research study suggests a novel approach for knee injury detection applying a crossbreed methodology combining radial kernel feature extraction and deep recurrent multilayer classification. Further it aims to boost the accuracy and efficiency of knee injury diagnosis through advanced computational techniques. Consequently, the initial step move to adaptive window median noise remove filter Pre-processing. Median-filtered values are used to recreate the signal, effectively removing noise while preserving signal features and adaptive window median filter dynamically adjusts the window size based on the local features of the signal and effectively remove the noise. Additional step, move to applying filtered Hybridization radial kernel segments are frequently overlapped and combined using approaches such as averaging or interpolation. Following step, move to High Dimensional Block feature extraction efficiently extracts important features from complex knee imaging data. Radial kernels are numerical functions used to measure the similarity between data points in a high-dimensional space. By applying radial kernel feature extraction, method identifies major patterns and structures within knee images and enabling better representation of acute information related to injuries. To conclude to Deep Recurrent Multilayer Classification Model allows for the accurate classification of knee injuries based on the extracted features, leveraging the hierarchical representation learned by way of multiple layers of processing and effectively enhanced knee injury detection and improve accuracy, smaller error rate and reduce knee injury detection time..

Keywords: *Hybridization radial kernel, Adaptive window median filter, Deep recurrent Multilayer, Hybridization block segmentation, Layer classification, Kernel feature extraction*

1. INTRODUCTION

Knee injury detection relies on a combination of clinical inquiry, patient history and medical imaging modalities such as X-rays, MRI (Magnetic Resonance Imaging), CT (Computed Tomography) scans, and ultrasound. These imaging techniques provide detailed information about the internal structures of the knee, allowing healthcare professionals to visualize and assess the extent of injuries accurately. It aims to enhance the accuracy and efficiency of knee injury detection. In this approach offers a comprehensive solution by effectively capturing relevant features and leveraging advanced classification algorithms, ultimately leading to improved diagnostic outcomes in knee injury detection. In [1]Three-Dimensional Knee Rotations likely focuses on developing methods or algorithms for accurately estimating the three-dimensional rotations of the knee joint. Accurate estimation of knee rotations is crucial for understanding normal joint function, diagnosing pathology, designing interventions and assessing treatment outcomes in conditions. [2]SKID (Self-Supervised Learning for Knee Injury Diagnosis) is a cutting-edge approach designed to diagnose knee injuries using MRI data. Allows for accurate and efficient diagnosis of various knee injuries, aiding healthcare professionals in providing timely and targeted treatment plans for

[1] April L, et al., “Towards Estimation of Three-Dimensional Knee Rotations” ***53rd Asilomar Conference on Signal, Systems, and Computers in 2019***, Asilomar, 2019, pp. 1359 - 1363.

[2] Siladittya Manna, et al., “SKID: Self-Supervised Learning for Knee Injury Diagnosis from MRI Data” ***Journal of IEEE Transactions On Artificial Intelligence***, vol. 00, no. 0, month 2020.

Patients

2. LITERATURE SURVEY

In [3] Dual-Mode Magnetic Resonance Imaging **(MRI)** Radiomics of the Knee Joint was a study initially exploring the viability of creating an automated model for detecting meniscus injuries using MRI radiomics. Peer review processes ensure the integrity of research outcomes in the field of medical imaging and diagnostics.

Fabella [4]is a small sesamoid bone located behind the knee joint and fractures involving this bone are relatively rare and uncommon injuries is crucial for healthcare professionals to accurately diagnose and treat patients with knee injuries. Anterior Cruciate Ligament **(ACL)** [5] pointed out the connection between ACL injuries and the development of osteoarthritis in the knee joint. In his research paper of injury and Osteoarthritis of the Knee It aimed at minimising the risk of osteoarthritis and optimizing outcomes for individuals with ACL injuries. Biomechanical Responses and Injury Characteristics [6]of Knee Joints under Longitudinal Impacts of Different Velocities" is a study that investigates how knee joints respond to longitudinal impacts at various velocities and examines the resulting injury characteristics, biomechanical responses and injury characteristics is essential for developing protective measures and injury prevention strategies.

Healthcare Data-Based Prediction Algorithm [7]for Potential Knee Joint Injury of Football Players" is a predictive model designed to forecast the likelihood of knee joint injuries among football players using healthcare data. By analysing this data, the algorithm aims to identify patterns and risk factors associated with knee injuries, enabling healthcare professionals. Knee Injury and Osteoarthritis Outcome Score **(KOOS),** [8]for patients with knee osteoarthritis in the Hong Kong cultural context. Further the study involves translating the original KOOS questionnaire into Cantonese and culturally adapting it to ensure its relevance and appropriateness for Hong Kong patients.

Augmented Reality **(AR)** [9] multimedia technology in remote postoperative rehabilitation for knee joint injuries. This technology likely involves interactive virtual environments or applications that guide patients through rehabilitation exercises and provide real-time feedback on their performance.

Diagnostic Value of Magnetic Resonance Image Feature Analysis [10] the usefulness of feature analysis techniques applied to Magnetic Resonance Imaging **(MRI)** data reconstructed using specific algorithms for diagnosing knee epiphyseal injuries. Pathophysiological Outcomes and Mechanisms of Tourniquet-Induced [11]The research survey of Ischemia-Reperfusion Injury during Total Knee Arthroplasty" is examining the potential physiological consequences and underlying mechanisms of Ischemia-Reperfusion Injury **(IRI)** caused by the use of a tourniquet during Total Knee Arthroplasty **(TKA).**

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[3] Y. Wang, et al., *"*Retracted: Feasibility of Constructing an Automatic Meniscus Injury Detection Model Based on Dual-Mode Magnetic Resonance Imaging (MRI) Radiomics of the Knee Joint*", **Computational and Mathematical Methods in Medicine,*** 27 September 2023.

[4] Taoufik Cherrad, et al., "Fracture of the Fabella: An Uncommon Injury in Knee", ***Case Reports in Orthopedics***,24 August 2015, p - 396710.

[5] David Simon, et al., "The Relationship between Anterior Cruciate Ligament Injury and Osteoarthritis of the Knee*" **Advances in orthopedics,*** 22 January 2015, p.928301.

[6] Yan Xiong, et al., *"*Biomechanical Responses and Injury Characteristics of Knee Joints under Longitudinal Impacts of Different Velocities", ***Applied Bionics and Biomechanics****,* 5 August 2018, p.1407345.

[7] Yue Yu and Zi Ye "Retracted: Healthcare Data-Based Prediction Algorithm for Potential Knee Joint Injury of Football Players", ***Journal of Healthcare Engineering,*** Volume 2023, 24 November 2021, p.3461648.

[8] Andy S. K. Cheng, et al., "Cross-Cultural Adaptation and Validation of the Hong KongVersion of the Knee Injury and Osteoarthritis Outcome Score (HK-KOOS) for Patients with Knee Osteoarthritis", ***Occupational Therapy International***, 14 August 2019, p.8270637.

[9] Ahmed Faeq Hussein, et al., "Effect of Remote-Control Augmented Reality Multimedia Technology for Postoperative Rehabilitation of Knee Joint Injury*"*, ***Computational and Mathematical Methods in Medicine***, 27 May 2022, p.9320063.

[10] M Pallikonda Rajasekaran, et al*.,* "Diagnostic Value of Magnetic Resonance Image Feature Analysis under Reconstruction Algorithm for Knee Epiphyseal Injury", ***Scientific Programming***, 25 January 2022, p. 1783975.

[11] Prangmalee Leurcharusmee, et al., "The Possible Pathophysiological Outcomes and Mechanisms of Tourniquet-Induced Ischemia-Reperfusion Injury during Total Knee Arthroplasty*"*, Oxidative ***Medicine and Cellular Longevit*,** 5 November 2018, p. 8087598.

The research study focuses on utilizing Three-Dimensional Computed Tomography **(3D-CT)** [12] reconstruction for the diagnosis and rehabilitation of ACL injuries in the knee joint. Further the study likely involves the creation of detailed 3D models of the knee joint from CT scans, which can provide enhanced visualization of the ACL and associated structures. Common peroneal nerve palsy [13] can lead to foot drop and sensory deficits, while multiple-ligament knee injury involves damage to two or more major ligaments, often resulting from trauma. Additionally, distal avulsion of the biceps femoris tendon affects the function of the hamstring muscles.

Knee Anterior Cruciate Ligament **(ACL)** [14]Injury involves evaluating the effectiveness of various k-space reconstruction techniques in visualizing ACL tears and assessing associated factors such as image resolution, signal-to-noise ratio and artifact reduction. Deep learning [15]Models on Medical Imaging Data to automatically detect and classify meniscus injuries based on image features.

Additionally, it might explore how arthroscopy, a minimally invasive surgical procedure used to visualize and diagnose internal joint structures. ACL [16]aims to demonstrate the efficiency and effectiveness of the deep learning approach in ACL detection and potentially offering improvements over traditional manual methods or rule-based algorithms. Knee Injury Detection Using Deep Learning [17]on MRI Studies aiming to provide insights into the current state-of-the-art in deep learning-based knee injury detection. Further it utilizes deep learning algorithms for diagnosing various knee injuries from MRI images. Efficiently-Layered Network **(ELNet)** [18] " likely introduces a novel deep learning architecture specifically designed for detecting knee injuries from MRI scans. ELNet is likely optimized for efficient processing of MRI data, with a focus on accurately identifying and localizing various types of knee injuries such as ligament tears, meniscus damage, or cartilage defects.

Knee Anterior Cruciate Ligament Injury [19] Caused by Exercise automatically extract relevant features from diagnostic images or patient data to inform personalized rehabilitation protocols. These protocols are then implemented to aid in the recovery and rehabilitation of individuals with ACL injuries caused by exercise.

Modified arthroscopic procedure [20] aimed to repairing the PCL avulsion fracture using sutures, with the goal of restoring stability and function to the knee joint. By focusing on arthroscopic techniques, minimally invasive surgery for treating complex knee injuries in adolescent patients.

3. METHODOLOGY

In this context, Knee injury data using hybridization and radial kernel functions. Hybridization could mean combining different feature extraction techniques or combining features from multiple sources (such as medical images, patient history, and others). Radial kernel functions are commonly used in machine learning for tasks like classification and regression particularly in Deep Recurrent Multilayer Classification and Kernelized Methods.

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[12] Shunchao Zhang, et al., "Diagnosis and Exercise Rehabilitation of Knee Joint Anterior Cruciate Ligament Injury Based on 3D-CT Reconstruction", ***Complexity***, 20 December 2023, p. 3690124.

[13] Takeshi Oshima, et al., "Common Peroneal Nerve Palsy with Multiple-Ligament Knee Injury and Distal Avulsion of the Biceps Femoris Tendon", ***Case Reports in Orthopedics,*** 19 April 2015, p. 306260.

[14] Rui Chang, et al., "K-Space Data Reconstruction Algorithm-Based MRI Diagnosis and Influencing Factors of Knee Anterior Cruciate Ligament Injury", **Contrast Media \& Molecular Imaging**, 1 June 2022, p.1711456.

[15] Zijian Li, et al., "Deep Learning-Based Image Feature with Arthroscopy-Aided Early Diagnosis and Treatment of Meniscus Injury of Knee Joint", ***Journal of Healthcare Engineering***, 17 September 2021, p.2254594.

[16] Mazhar Javed, et al., "Efficient Detection of Knee Anterior Cruciate Ligament from Magnetic Resonance Imaging Using Deep Learning Approach", ***Diagnostics,*** 11 January 2021, p. 105.

[17] Athanasios Siouras, et al., "Knee Injury Detection Using Deep Learning on MRI Studies: A Systematic Review", ***Diagnostics***,19 February 2022, p.537.

[18] Tsai C.H., N. et al., "Knee Injury Detection using MRI with Eciently-Layered Network (ELNet)" Proceedings of Machine Learning Research, ***Medical Imaging with Deep Learning***,1(11, 2020), pp. 784 - 794.

[19] Sibo Zhu, Jie Gao., "Effect of Rehabilitation Training Based on Automatic Extraction Algorithm on Knee Anterior Cruciate Ligament Injury Caused by Exercise", ***Scanning***, 21 June 2023, p. 8304071.

[20] Miguel Quesado, et al., "Modified Arthroscopic Suture Fixation of Posterior Cruciate Ligament Tibial Avulsion Fracture in the Setting of Multiligament Knee Injury in Teenager", ***Case Reports in Orthopedics***, 19 July 2021, p. 3626276.

Deep learning architecture for classification tasks related to knee injury detection. "Deep" implies multiple layers in the neural network allowing it to learn hierarchical representations of the input data. "Recurrent" likely refers to the presence of Recurrent Neural Network **(RNN)** layers, which are effective for processing sequential data or data with temporal dependencies. "Multilayer Classification" indicates that, the model is designed to classify knee injury data into multiple classes or categories.

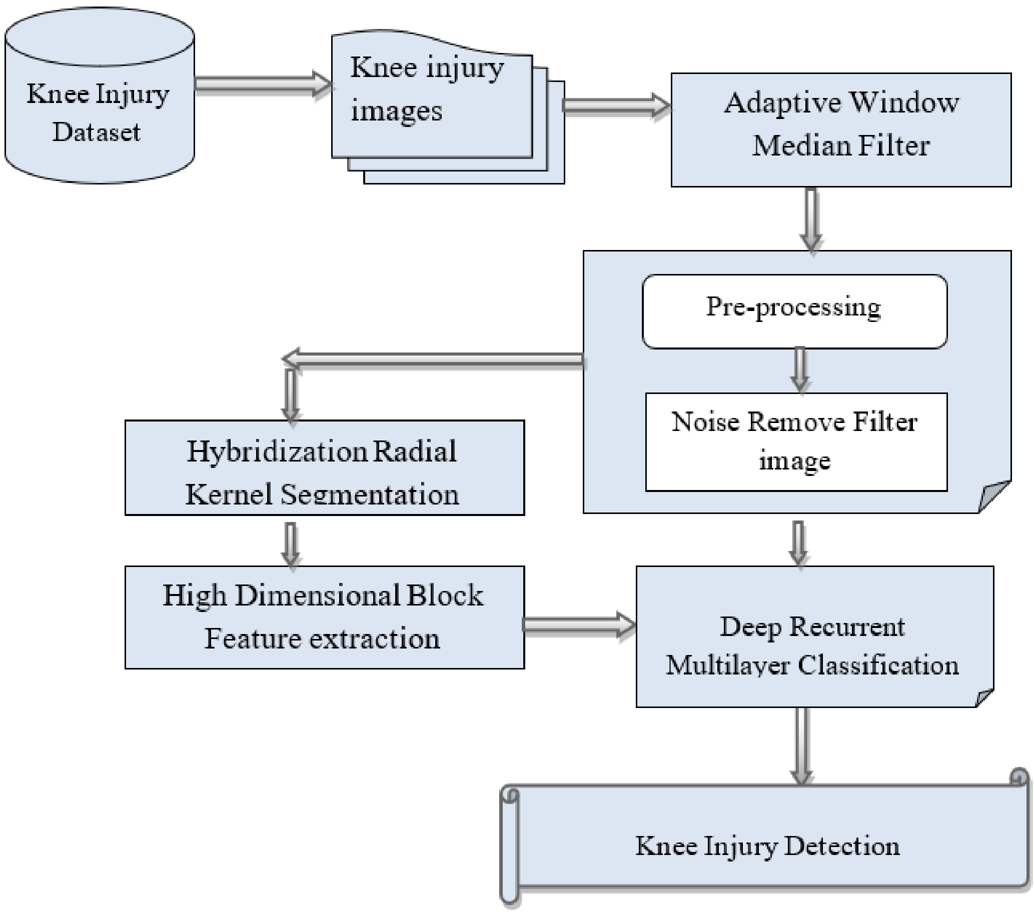

Figure 1 Architecture Diagram of the Proposed Hybridization Radial Kernel Feature Extraction and Deep Recurrent Multilayer Classification for Knee Injury Detection (HRKFDRMLC)

Knee injury detection leverages both traditional machine learning techniques (such as feature extraction using radial kernel functions) and deep learning methods (such as recurrent neural networks for classification). The hybrid approach could potentially offer better performance by exploiting the strengths of both types of techniques and handling different aspects of the data effectively.

Adaptive Window Median Filter

An adaptive window median filter is a type of signal processing technique used to remove noise from a signal while preserving the sharpness of edges or important features. Unlike traditional median filters which use a fixed window size for filtering, adaptive window median filters adjust the size of the window based on local characteristics of the signal. This adaptability allows for better noise reduction in areas with varying levels of noise or signal complexity.

$$y[n] = Median\{x[n - \frac{\mathrm{W(n)}}{2} + 1] \ldots \ldots Equ\ (3.1)$$

Where above equ (3.1) x[n] represent input signal at sample index n, y[n] represent output signal after filtering. W[n] represent adaptive window size at sample index n. Median calculates the median value of the elements within the adaptive window.

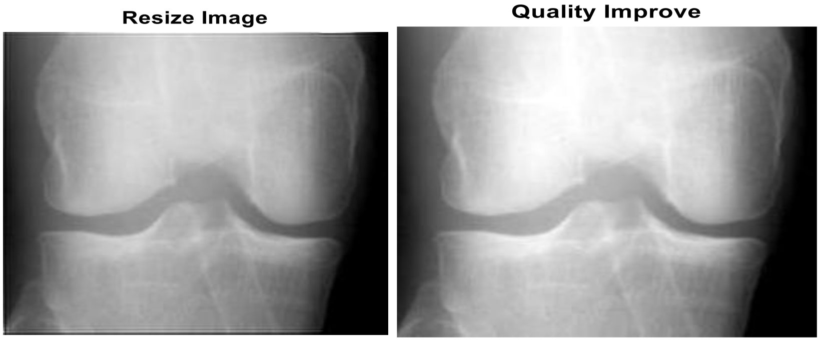

Figure 2 Adaptive window median Filter

The key aspect of the adaptive window median filter is the dynamic adjustment of the window size **W(n)** based on the local characteristics of the signal. This adjustment could be based on various criteria, such as local signal variance, gradient magnitude or other statistical measures. By adaptively changing the window size, the filter can effectively suppress noise while preserving important signal features.

The specific method for determining **W(n)** could vary depending on the application and the desired characteristics of the filter. Common approaches include using fixed percentages of the signal length, local signal statistics or heuristics based on the properties of the noise and signal.

Hybridization Radial Kernel Segmentation

The implementation of hybridization radial kernal block segmentation has allowable for the breakdown of images into smaller, more wieldy segments or blocks. This process enables precise localization of disease-affected areas, even in complex and overlapping regions and in knee injury.

This segmentation is particularly effective for handling complex patterns and variations in knee injury size, orientations and disease manifestations. By analysing the image at several scales, hierarchical segmentation confirms that both fine-grained details and broader structural features are captured, developing the accuracy of disease detection.

Multi-Scale Block Division

The knee injury is divided into hierarchical blocks at different scales. For a given image I, the block division at scale could be represented as:

$$\boldsymbol{B_s = Divide.(\mathrm{I}, s) \ldots Equ\ 3.2}$$

Where above equation 3.2 I represent the input image and **"S"** is the scale parameter (e.g., Block size) and "$\boldsymbol{B_s}$" represent the set of blocks at scale at **"S".**

Segment Block Aggregation

Segment block aggregation from each block is aggregated to form a comprehensive representation of the image. This could be expressed as:

$$\mathrm{F} = \sum_{i=1}^{N} \boldsymbol{Segment\ Block\ Aggregation} * \boldsymbol{B_i \ldots Equ\ 3.3}$$

Where above equation 3.3 "$\boldsymbol{B_i}$" represent the **'i'** th block Extract Features is a function to extract segment from each block and **"F"** is the aggregated segment block representation.

By leveraging hierarchical segmentation, the system realizes more accurate and robust disease detection, ensuring that even knee injury disease patterns are identified.

This approach enhances the overall performance of the knee injury disease detection pipeline, making it a vital component of our proposed methodology.

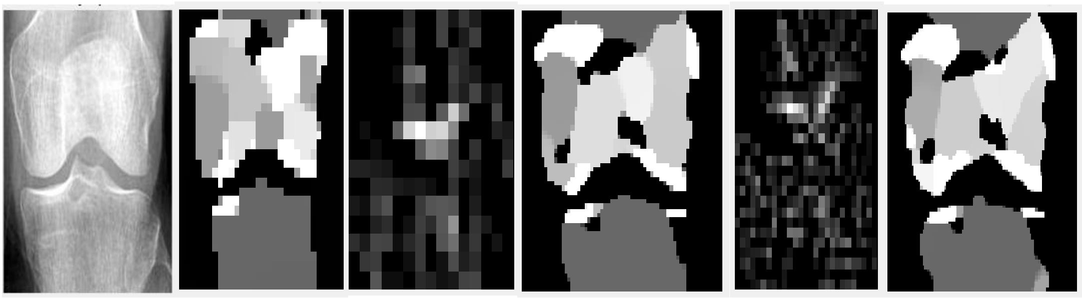

Figure 3 Hybridization Radial Kernel Segmentation

High Dimensional Block Feature Extraction

High dimensional block in feature extraction typically refers to combining multiple feature extraction techniques or sources of data to capture a more comprehensive representation of the underlying patterns in the data. In the context of knee injury detection, this could involve integrating various types of data sources such as medical images (MRI, X-ray), clinical reports, patient history, biomechanical data, and others. Hybridization allows for a richer feature set that may better capture the complexities of knee injury patterns.

Radial kernel functions are mathematical functions commonly used in machine learning for tasks like classification and regression. In feature extraction, radial kernels could be applied to transform the input data into a higher-dimensional space where the data becomes linearly separable or exhibits clearer patterns. Particularly, Radial kernels are particularly useful for capturing nonlinear relationships in the data. Examples of radial kernel functions include gaussian Radial Basis Functions (**RBF**) and Laplacian radial basis functions.

Applying radial kernel functions to transform the hybridized data into a higher-dimensional feature space. Extracting features from the transformed data that effectively capture the distinguishing characteristics of knee injuries. Selecting or designing an appropriate classifier (such as a Support Vector Machine, neural network, and others) to utilize these features for knee injury detection.

Hybridization with radial kernel feature extraction is to enhance the discriminative power of the extracted features like leading to more accurate knee injury detection models. This approach leverages both the richness of multiple data sources and the nonlinear mapping capabilities of radial kernel functions to improve the performance of knee injury detection systems.

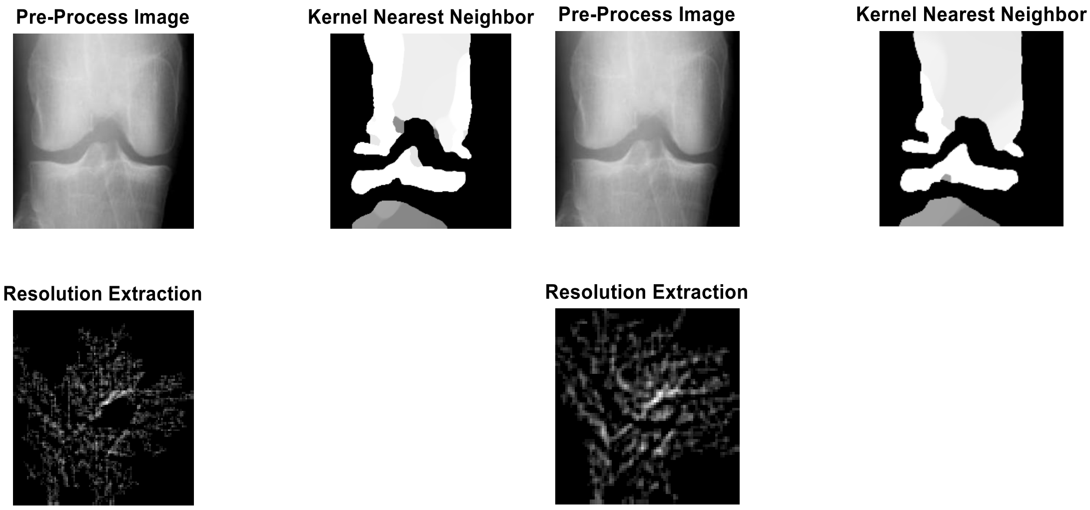

Figure 4 High Dimensional Feature Extraction

let **X** represent the hybridized data matrix, where each row corresponds to a sample (e.g., a patient) and each column represents a feature obtained from different sources. The hybridization process can be represented as:

$$X = [X1, X2, \ldots Xm] \ldots\ldots \boldsymbol{Equ}\ (\mathbf{3.4})$$

Where **X1,X2,...XM** are the individual feature matrices obtained from different data sources or extraction techniques.

Once the data is hybridized, radial kernel functions can be applied to transform the hybridized data into a higher-dimensional feature space. Let $\phi(\cdot)$ represent the radial kernel function. The transformed feature matrix Z can be calculated as

$$Z = [\phi(X1), \phi(X2), \dots \phi(Xm)] \dots\dots \boldsymbol{Equ\ (3.5)}$$

Each $\phi(xi)$ represents the application of the radial kernel function to the features obtained from the "**i**- th" data source

The process involves hybridizing data from various sources, applying radial kernel functions to transform the hybridized data into a higher-dimensional space, combining the features obtained from different sources and finally using these features for knee injury detection through classification. This approach aims to leverage the complementary information from different data sources and the nonlinear mapping capabilities of radial kernel functions to improve the accuracy of knee injury detection models.

A "High Dimensional Block" is a subset of data from a dataset that encompasses a large number of dimensions or features.

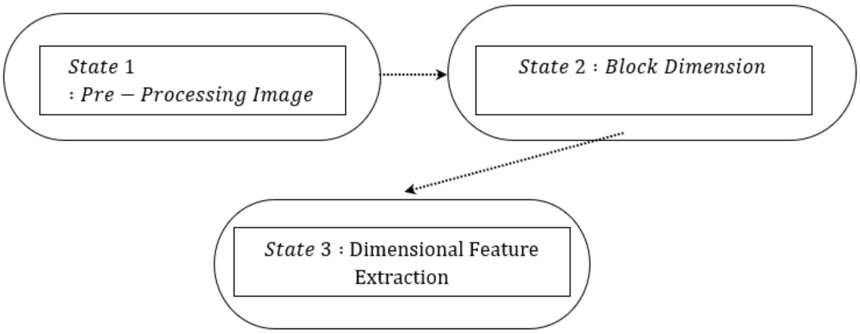

Figure 5 High Dimensional Block Feature Extraction

Let's denote the dataset as **D** where each data point has $\boldsymbol{N}$ dimensions or features. A high-dimensional block can be represented by selecting a contiguous subset of dimensions within the dataset. If we denote this subset as $\boldsymbol{B}$, then the high-dimensional block $\boldsymbol{B}$ can be represented as:

B = {x $_{i1}$, x $_{i2,....}$ x $_{ik}$ }…Equ 3.6

Where x_i represents the "**j** - th" dimension or feature selected from the dataset **D** and **k** represents the number of dimensions included in the block. This notation implies that the block **B** contains k dimensions selected from the original dataset **D**.

High-dimensional blocks from a dataset could vary depending on the specific task or analysis being performed. For example, in feature selection or dimensionality reduction tasks, one might select high-dimensional blocks to identify subsets of features that are most relevant to the problem at hand. In signal processing, high-dimensional blocks might be selected to analyse patterns or structures that span multiple dimensions in the data.

Deep Recurrent Multilayer Classification

Deep Recurrent Multilayer Classification **(DRMC)** for knee injury detection is a sophisticated approach that utilizes deep learning techniques, Specifically Recurrent Neural Networks **(RNNs),** to classify knee injury from medical imaging data such as MRI scans or X-rays.

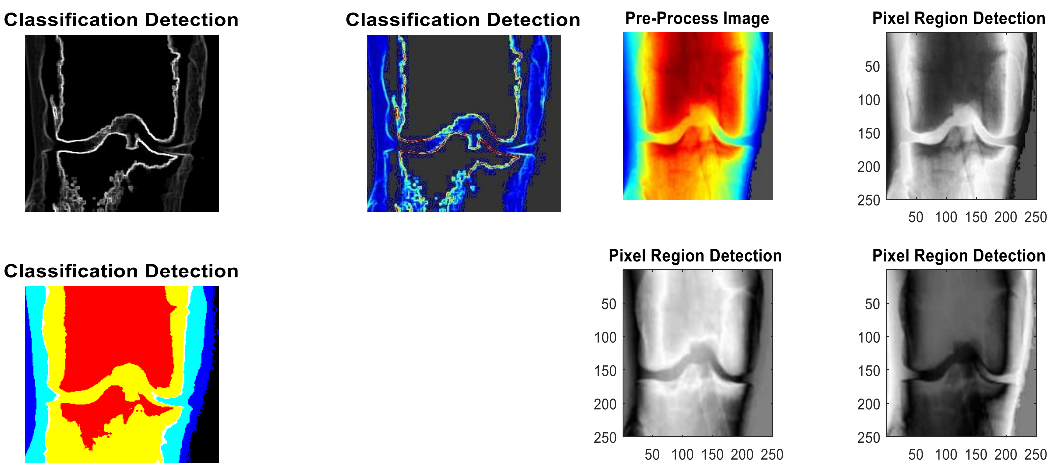

Figure 6 Deep Recurrent Multilayer Pixel Region Classification

DRMC leverages the hierarchical representations learned by deep recurrent networks to capture temporal dependencies in sequential medical data, such as time-series information extracted from MRI scans or X-ray images of knee joints. The multilayer architecture enables the model to learn increasingly abstract features at different levels of the network allowing it to discriminate between healthy knees and those with various types of injuries such as ligament tears, meniscus damage or cartilage degradation.

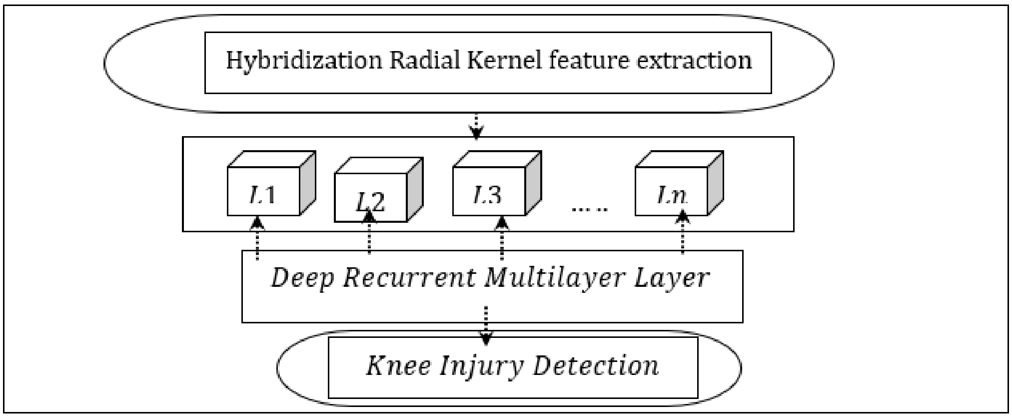

Figure 7 Deep Recurrent Multilayer Classification

DRMC involves the recurrent computation within the **RNN** layers. Let's represent the hidden state of the "i" -th layer at time step t as $hi(t)$. The computation of the hidden state in an **RNN** layer can be expressed as follows:

$$\mathbf{h_i(t) = f\,(W_i \,.\, x(t) + U_i \,.\, h_i(t-1) + b_i)}\ldots \textbf{ Equ 3.7}$$

Where $\mathbf{h_i(t)}$ is the hidden state of the "i"-th layer at time step t. f is the activation function, such as the hyperbolic Tangent **(tanh)** or Rectified Linear Unit **(ReLU).** $\mathbf{W_i}$ is the weight matrix that connects the input **x(t)** to the hidden state . $\mathbf{h_i(t)}$

$\mathbf{U_i}$ is the weight matrix that connects the previous hidden state $\mathbf{h_i(t-1)}$ to the current hidden state $\mathbf{h_i(t)}$. $\mathbf{b_i}$ bias vector, **x(t)** is the input at time step t.

Above equation represents the recurrent computation within each layer of the **RNN**, capturing temporal dependencies in the input data. The output of the final layer could be fed into a softmax classifier for knee injury classification.

DRMC involves training the model on a dataset of labeled knee images, optimizing the network parameters (weights and biases) using techniques like Back Propagation Through Time **(BPTT)** or gradient descent, and evaluating its performance on unseen test data to assess its accuracy in detecting knee injuries.

Input: Knee Osteoarthritis Image **Output**: Efficiently knee injury detection
Step 1: **Begin** Step 2: **For** each Adaptive window median noise filter Step 3: x[n]-input y[n]-output of median filter using equation (3.1) Step 4: **For** each hybridized data matrix of size $X1\ X2 \ldots X\ n$ Step 5: Obtain Deep recurrent Multilayer using equation (3.4) with respect to activation function Step 6: Measure high-dimensional spaces classified normal or abnormal using equation (3.5) Step 7: Efficiently detect knee injury classification vector block negative -1 or positive +1 (3.6) Step 8: **End for** Step 9: **End for** Step 10: **End**

Algorithm1 Algorithmic process of High Dimensional Block Feature Extraction and Deep Recurrent Multilayer Classification for Knee Injury Detection (HRKFDRMLC)

Deep Recurrent Multilayer a powerful supervised learning algorithm used for classification and regression tasks.

Classification effectiveness lies in its ability to generalize well to unseen data and its robustness to over fitting, especially in cases where the number of features exceeds the number of samples.

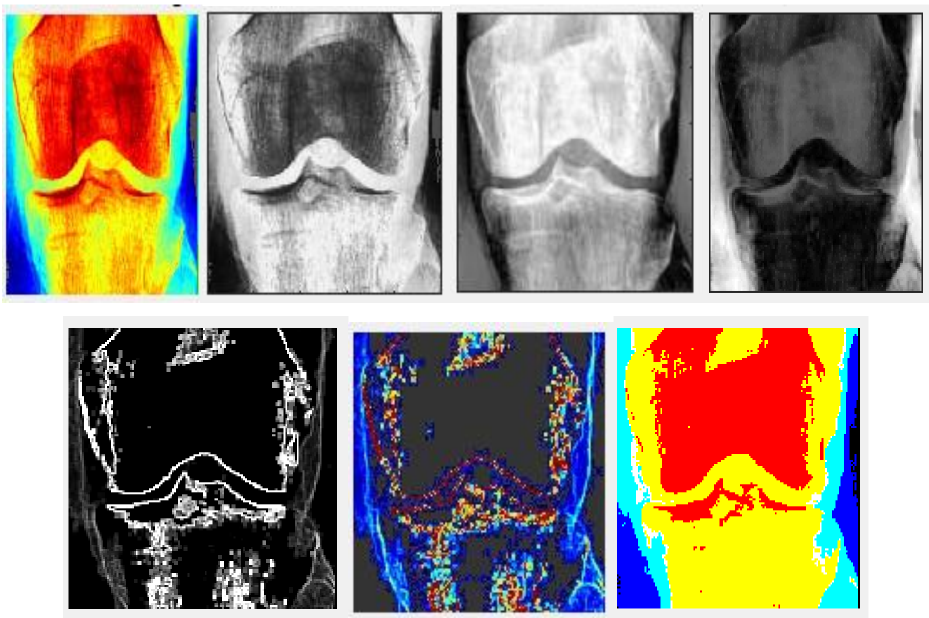

Figure 8 Deep Recurrent Multilayer Knee Injury Detection Classification

Classification works by finding the optimal hyperplane that separates data points of different classes with the maximum margin. It aims to maximize the distance between the hyperplane and the nearest data points of each class, known as support vectors. SVM is effective even in high-dimensional spaces and is versatile in handling various types of data through different kernel functions, allowing it to capture complex relationships between features.

The decision function of an classification can be expressed as:

f(x) = sign (W, . X + b)….Equ (3.8)

f(x) is the decision function that assigns a class label to input **x**. **W** is the weight vector, **X** is the input feature vector. b is the bias term, sign is the sign function that returns **+1** for positive values and **-1** for negative values.

The optimal hyperplane is determined by finding the weights **(w)** and bias **(b)** that maximize the margin between classes while satisfying the constraint

y_i (w, . x_i + b >1)….Equ (3.9)

where **y_i** is the class label of the **"i-th"** data point, and x_i is its feature vector.

Decision function **(x)** assigns class labels based on the sign of the result. In regression tasks, SVM aims to fit a hyperplane that predicts continuous target values.

Experimental Settings

Knee Osteoarthritis Dataset KL Grading–2018 dataset brings out the details.[21] The high-resolution Knee Osteoarthritis Images are collected under a variety of imaging conditions that affect the visual appearance of the left and right knee legs and the data. Collected from 4796 participants. The dataset consists of 4130 X-Ray images for classification of knee injuries with a scale of 0 to 4 such as Healthy Knee Images, Doubtful, Minimal, Moderate and Severe.

It could include patient demographics gender medical history, details of knee pain and symptoms, and any treatments or interventions received. Typically, It includes medical images such as X-rays of the knee joint. These images might be labeled with information about the severity of osteoarthritis, specific features of interest or annotations by medical professionals.

4. RESULT AND DISCUSSION

Accuracy

Accuracy is a measure of how a diagnostic test correctly identifies both positive and negative cases among all cases examined. It is calculated as the ratio of correctly identified cases (both true positives and true negatives) to the total number of cases

[21] https://www.kaggle.com/datasets/tommyngx/kneeoa

examined.

Accuracy measures the overall correctness of the diagnostic test with considering both true positives and true negatives. It is calculated as:

$$Accuracy = \frac{\text{True Positive+True Negative}}{\text{No of Input Images}} \quad \text{.... Equ 5.1}$$

Table 1 Accuracy of Hybrid Radial Kernel Feature Deep Recurrent Multilayer Classification (HRKFDRMLC)

No of Knee Osteoarthritis Image	Accuracy (%)		
	HRKFDRMLC	ACL	SKID
50	95	88	86
100	93	85	81
150	95	81	79
200	92	84	82
250	93	82	80
300	94	83	79
350	97	85	80
400	94	83	81
450	96	87	83
500	95	89	84

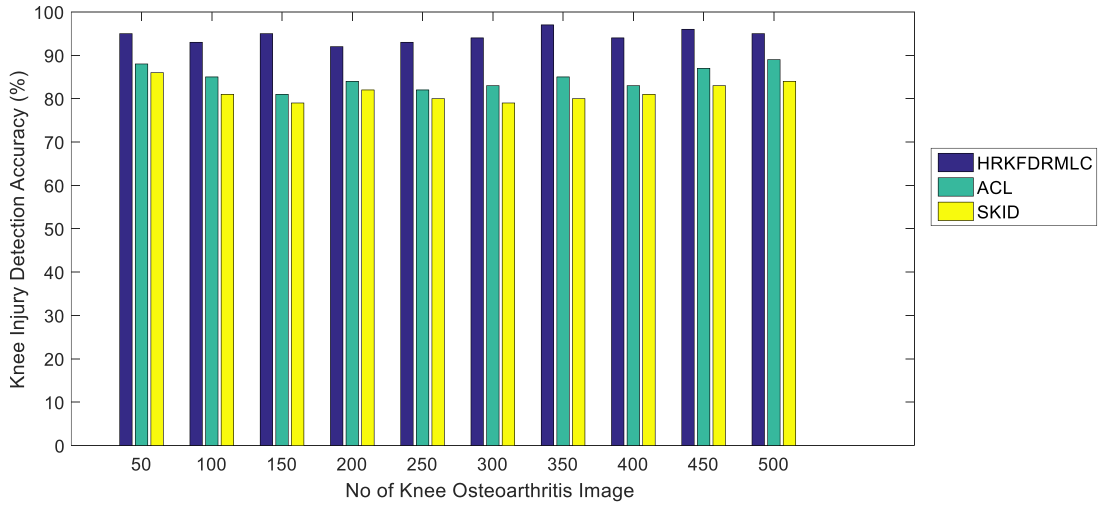

Figure 8 Knee injury detection accuracy

Error Rate

The knee injury detection error rate, often referred to as misclassification rate and it is a measure of how often the diagnostic test incorrectly identifies cases as positive or negative. It is calculated as the ratio of incorrectly identified cases (false positives and false negatives) to the total number of cases examined. Mathematically,

The knee injury detection error rate can be expressed as Follow equation

$$Error\ rate = \frac{\text{False Positive+False Negative}}{\text{No of Input Images}} \quad \text{.... Equ 5.2}$$

Table 2 Error Rate of Hybrid Radial Kernel Feature Deep Recurrent Multilayer Classification (HRKFDRMLC)

No of Knee Osteoarthritis Image	Error Rate (%)		
	HRKFDRMLC	ACL	SKID
50	15	28	36
100	23	35	38
150	35	41	49
200	42	44	52
250	53	52	60
300	54	57	69
350	57	65	70
400	64	73	84
450	66	77	87
500	67	79	89

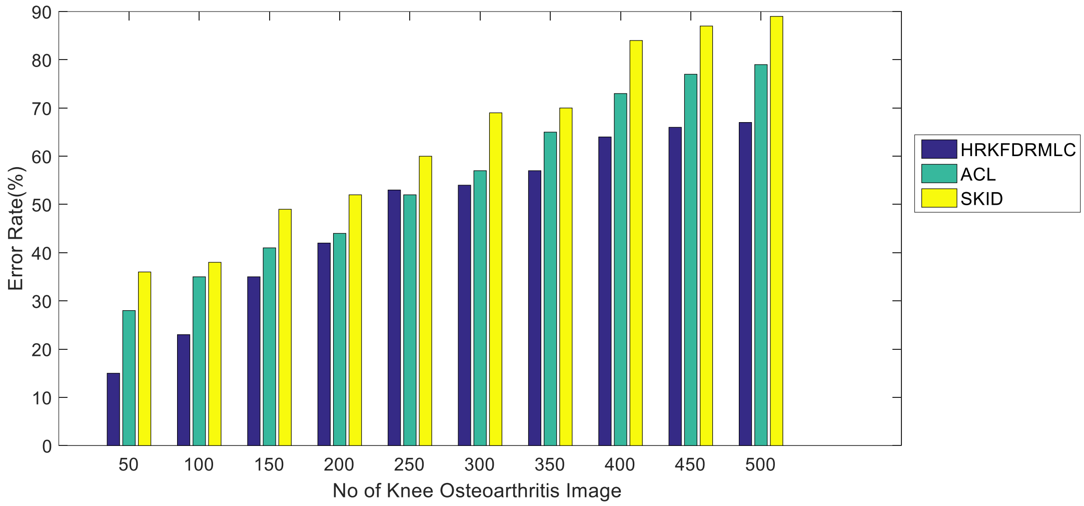

Figure 9 knee injury Detection Error rate (%)

Detection Time (MS)

Detection time is evaluated in Milliseconds **(MS)** and formalized as follows.

$DT = N * time\ (predicting\ one\ image\ )$ ……. **Eqn (5.4)**

From equation (5.4), prediction time 'DT' is estimated. Here, 'N' represents the number of images. This equation multiply time of injury from the time of diagnosis to determine the duration it took to detect the knee injury.

Table 3 Detection Time (MS) of Hybrid Radial Kernel Feature Deep Recurrent Multilayer Classification (HRKFDRMLC)

No of Knee Osteoarthritis Image	Detection time (ms)		
	HRKFDRMLC	ACL	SKID

50	35	38	56
100	33	35	51
150	45	51	59
200	52	54	64
250	55	58	68
300	58	67	69
350	60	75	80
400	66	83	83
450	69	87	87
500	70	89	90

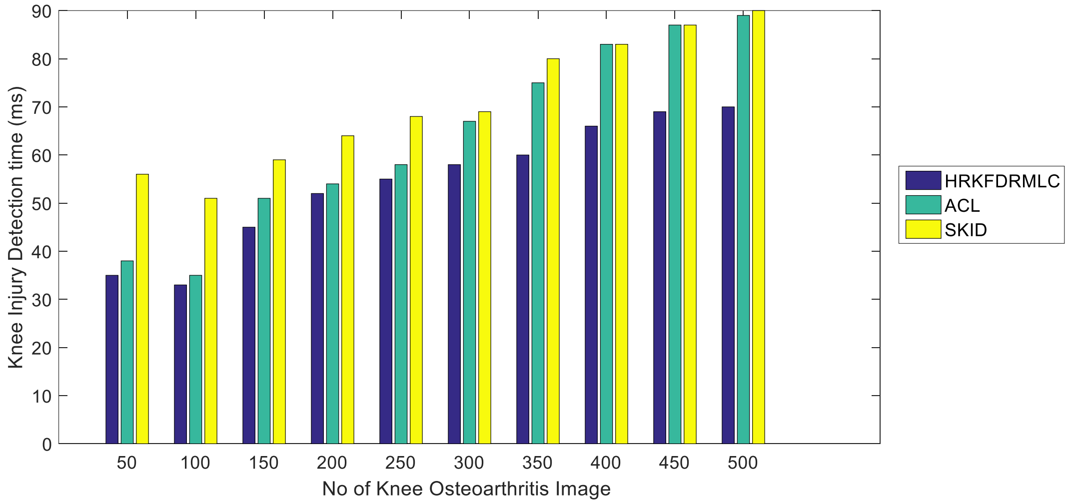

Figure 10 Knee Injury Detection Time (ms)

5. CONCLUSION

A knee Osteoarthritis images detection algorithm is developed through this research for identifying the injury detection from the Osteoarthritis images by proposing the hybridization radial kernel feature extraction and deep recurrent multilayer classification represents a significant advancement in knee injury detection **(HRKFDRMLC)** method. It Proposed methodology encompasses various stages, including preprocessing, feature extraction and classification, providing a comprehensive framework for knee injury detection. By addressing each stage with tailored techniques, the method ensures thorough analysis and accurate identification of abnormalities First step adaptive window median noise removal filter in the preprocessing stage effectively removes noise from the signal while preserving important signal features. This noise reduction step enhances the quality of the data, leading to more robust and reliable results. Radial kernel feature extraction method efficiently identifies relevant patterns and structures within knee imaging data, leading to more accurate representations of critical information related to injuries. It enhanced accuracy contributes to more reliable diagnoses. Deep recurrent multilayer classification model allows for precise classification of knee injuries based on the extracted features. By leveraging hierarchical representations learned through multiple layers of processing, the method achieves improved efficiency in knee injury detection, reducing error rates and minimizing detection time. The research study demonstrates the potential of advanced computational techniques in improving the accuracy and efficiency of knee injury detection. By integrating hybridization radial kernel feature extraction and deep recurrent multilayer classification, we pave the way for more effective diagnostic tools and better patient outcomes in the field of orthopedics