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Median Kernel based Multi-Wavelet Feature Extraction and Multimodal fireflyOptimization and Learning Classification (MMFOLC) knee injury detection

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ABSTRACT

Knee injuries are not easy to correctly diagnose. Knee injury has bad reaction on medical treatment and if the knee injury are not detected beginning stage, it will result in a growth in pain insecure. Increase cost relies on lots of subjective factors such as physician experience, swelling, patient guarding and the severity of the injury. Knee Injuries are the main cause of athlete's players and can occur during the knee accident day to day activities. a physician manually manipulates the knee with a series of standard tests as well as knee injury increase the treatment cost. Our Proposed technique MMFOLC includes three type of process Median kernel Filter(MKF) pre-process and segment, Multi-wavelet feature extraction and Multimodal firefly optimization injury detection and classification. In Median kernel filter pre-processing technique decrease the noise image pixel and improve the image clearness quality. Second step move to the kernel image block segmentation it is used for reduce the error find knee injury detection in pixel based block segmentation. Next step Multi-wavelet feature extraction (MWFE) for detect knee injury unhealthy pixel detection shape and wavelet signal feature extraction its minimize the error and time consumption to detect the knee injury. Finallyused Multimodal Firefly Optimization technique(MMFOLC) accurate Learning classify and detect the injury of Knee. this technique improve classification accuracy and reduce error ratecompare with existing methods. Experimental evaluation of MMFO technique is carried out using a Knee injury data with different performance metrics such as accuracy, Prediction time,and true positive rate with respect to a number of Knee Osteoarthritis images

Keywords: Knee Injury Detection, Median filtering, kernel block segmentation, Multiwavelet Feature Extraction, Multimodal Firefly Optimization Learning technique.

1. Introduction

The knee injury is one of the risky and most important causes of knee joint pain and injury in adults and sports children. The early and exact diagnosis of knee injury is significant for the earlier treatment process. It is a significant step for an expert to identify a knee injury. A highly developed medical imaging system uses Magnetic resonance imaging (MRI) and X-ray images for fast and accurate classification to provide the exact medicine treatment for a

injury-affected person. Many researchers carried out their research for knee pain andinjury detection at an earlier stage.

Deep learning method was implemented in [1]for the process of human-level decision-making tasks to the MRI-based identification of knee injuries. However, the enhanced treatment of knee injuries significantlyprovides the accurate and cost-effective recognition. In [2],the Efficiently Layered Network (ELNet), a convolutional neural network (CNN) architecture employedto the initial knee MRI investigationof triage.Magnetic Resonance Imaging (MRI) was the imaging methodto detect the knee injury. Though, thebenefit of obtaining knee construction in three dimensions radiologists to find the potential tears within the knee.

1.1 Objectives

- To propose an automated system for detecting knee injury and pain from Knee Osteoarthritis images employing different Multi-wavelet signal feature (MWSf)and Firefly optimization and classification techniques

- To improve the classification accuracy by using various subband signal extraction firefly optimization and Learning classification methods

- Analyze the wavelet signal feature and firefly optimization sub-band signals with the testing normal and knee injury features

- Minimize time consumption and error rate and increase detection accuracy

- Compare the efficiency of the proposed and existing methods

- The proposed MMFOLC technique with the various algorithms to discuss the performance with different metrics parameters .

2. LITERATURE SURVEY:

Automated scheme was implemented in [3] to demonstrate the knee MRI which supports the clinicians prioritize patients byimproved risk and make effective, more accurate diagnoses. However, designed method performs the deep learning schemes capable of learningthe layers of features and displaying the dynamic associationsamong medical images and analyses.'MPFuseNet' network and Area Under the Curve (AUC) scores was intended in [4] to find the Anterior Cruciate Ligament (ACL) tears and Abnormal MRIs. Multi-view Convolutional Neural Network (CNN) using the spatial attention block forenhancing the knee injury recognition. An open-source Magnetic Resonance Imaging (MRI) data set using the image-level labels was leveraged for this evaluation.

Machine learning methods was presented in [5] to obtain thesignificant data for exhibiting the difficult patterns of knee MRI.However, the designed method provides the various issue ofexcessivemeasure of featurethrough MRIs is difficult to interpret and time consuming for radiologists. However, designed method are required to analysethe significant number of MRIs within short interval.Infrared thermography (IT) and convolutional neural networks (CNNs) was proposed in [6] to distinguishamong healthy knee and injured knee, to improve the medical specialists. Knee injury is thegeneral health issue which influences people who practice sports and those who do not do it. However, designed method provides betteroccurrence of knee injuries givesthe considerable impact on the health-related life qualityof patients.

Self-supervised learning (SSL) methodwas designed in [7] for learning the spatial anatomical descriptionsover the frames of magnetic resonance (MR) video clips to the detection of knee medical situation. Though, the efficiency and consistency of the pretext representation in learning representations of minority classes without utilizing the strategy towards imbalance in the dataset.In medical image analysis, the cost of achieving high-quality data and annotation by experts is a barrier within various medical applications.Magnetic Resonance Imaging (MRI) were employed in [8] for the fixed number of slices or 2D images over every axial, coronal and sagittal planes to combine the three planes within one multi-plane network.Depend on deep learning, the comparative performances of transfer learning and deep residual network trained were developed from scratch. However, transfer learning and precisely tuned data augmentation scheme were the vital task for maintaining the finest performance.

A novel ResNet50 scheme was implemented in [9] for detecting the disease or abnormalities, independent of the ResNet50 model. However, designed method aimed to creäteincreasinglyperforming deep learning technique that could identify meniscus damages, anterior cruciate ligament (ACL) tears and knee abnormalities within magnetic resonance imaging (MRI).However, designed method used to identify the anterior cruciate ligament injury through efficient automatic magnetic resonance imaging without involving radiologists, of deep learning technique. In [10], customized 14 layers ResNet-14 construction of convolutional neural network (CNN) using various directions by class balancing and data augmentation.However, designed method of analytical results indicated to identify and estimate ACL injuries within athletes using the deep-learning model.

The prevalence of magnetic resonance imaging (MRI) was investigated in [11] for findingtheir relationship using knee symptoms within women without radiographic evidence of knee osteoarthritis (KOA).Logistic regression analysis was achieved for estimating the relationship among MRI abnormalities and knee symptoms. In [12], Dynamic knee laxity tests are more difficultforfinding the novel solution of universal analysis. However, the hypothesis permits to attain the more accurate and robust non-invasive diagnostic technique with three laxity thresholdson Artificial Intelligence (AI).

In [13], the knee joint achieves the most frequent anatomical injury location accounting for one-third of everyinjurywithin recreational alpine skiers. However, comprehensive data on existing knee injury patterns within the populations was sparse. In [14], anterior knee symptoms wererequired in [14], for the competence of patellofemoral scores employedseparately. However, designed method used to assess the distribution of patellofemoral scores over the uniform cohort and examine the external authority and capabilityfor identifying the anterior knee symptoms within floor and ceiling effects.Though, aiming to observe anterior knee symptoms forassociating scoring systems to patellofemoral- related items compared tothe employment of patellofemoral scores to their ceiling effects.

Knee osteoarthritis (KOA) severity was calculatedin [15] with the Kellgren-Lawrence grade (KLG) scores. To explain the association among medial meniscus extrusion on ultrasonography (MMEUS) and prevalence of medial meniscus posterior root tear identifiedusing magnetic resonance imaging (MMPRTMRI). However, everyparticipant had medial knee pain without a knee trauma or surgery record. In [16], the tibiofemoral bone bruise patterns were analysedin MLKIs with and without peroneal nerve injury.Tibiofemoral bone bruise patterns observed on magnetic resonance imaging (MRI) which are associated using ligamentous injuries within the acutely injured knee. In multiligament knee injuries (MLKIs), Bone bruise patterns and specificallyinvolvementusing common peroneal nerve (CPN) injuriesare not well illustrated.

Knee pain was calculated in [17] using lower muscle strength and contribute to disability. Peripheral and central neurological mechanisms influence to OA pain. Identification of the relative contributions to muscle strength might improve thepotential treatments.Weaker baseline and year 1 handgrip strength was also correlatedusing better baseline CAPF. Weakerbaseline quadriceps strength was linkedusing radiographic scores within bivariate but not modified. In [18], the identification and organization of merged anterior cruciate ligament (ACL) and medial collateral ligament (MCL) injuries have been a controversial for variouseras.Though, controversy exists on the optimal method of treating a shared ACL usingbetter grade MCL injuries.

Deep learning technique were introduced in [19] for the automatic MRI interpreter. MRNet public dataset wasrecognized using the knee injury dataset comprise the multi-view MRI images of multi-label classification.Though, the tailored multi-label classification network using the improved data and feature fusion.Knee pain and osteoarthritis (OA) were measured in [20] to the incapacitybetween older adults. Though, it applies the varyingmeasuresto classify the knee OA populations.

Gait monitoring were intended in [21] for the more attention in gait analysis forvalidating the potential developments of minimal limb disorders. However, existing vision and floor sensor-based models have the restrictions of operational issue and higher cost whichmake uncomfortable for specific use.Electromagnetic method was developed in [22] on themultistatic radar to image knee injuries.However, the better rate of knee injuries between athletes and other people for the onsite recognition to prevent severe ligament tear emphasize the requirement of portable knee imaging tool.

In [23], the arthroscopic clinical were demonstrated in [23] for analysing the patients treatment using pathologic hypertrophy of the synovium within anteromedial joint sectionof anteromedial knee pain.Pathologic hypertrophy of the synovium within the anteromedial joint compartment outcomes the trauma which cause mild chondromalacia changes within medial femoral condyle and knee pain. Arthroscopic debridement of this pathologic tissue considerablyenhances the symptoms. Auxiliary diagnosis of the knee joint sports was carried out in [24] using the injury detection model. Though, machine learning-based rehabilitation physical training can significantly enhance the athletes' endurance on balance mats and enhance knee function scores.Magnetic resonance imaging (MRI) were presented in [25] for the estimation of knee injuries, however, the accuracy of MRI used forgrouping the multiple ligament knee injuries (MLKIs) remains unidentified. MRI is beneficialfor early recognition and detection of acute MLKIs, though, the accuracy of MRI organizing MLKIs is restricted.

3. Median kernel image pre-processing :

Therefore, the proposed MMFOLC technique uses Median kernel Interval Filtering to remove the noise from the image. The proposed Median kernel Filtering is used to consider the maximum likelihood location estimation for identifying the noisy pixels. the preprocessing step is necessary for image processing to improve the quality of the image by removing the noise. The number of collected natural images from the dataset is Img_1 , Img_2, Img_3 … Img_n and each image comprises the number of pixels P_1, P_2, P_3 … P_m. The designed filtering technique employs the series of measurements examined over time including statistical noise.

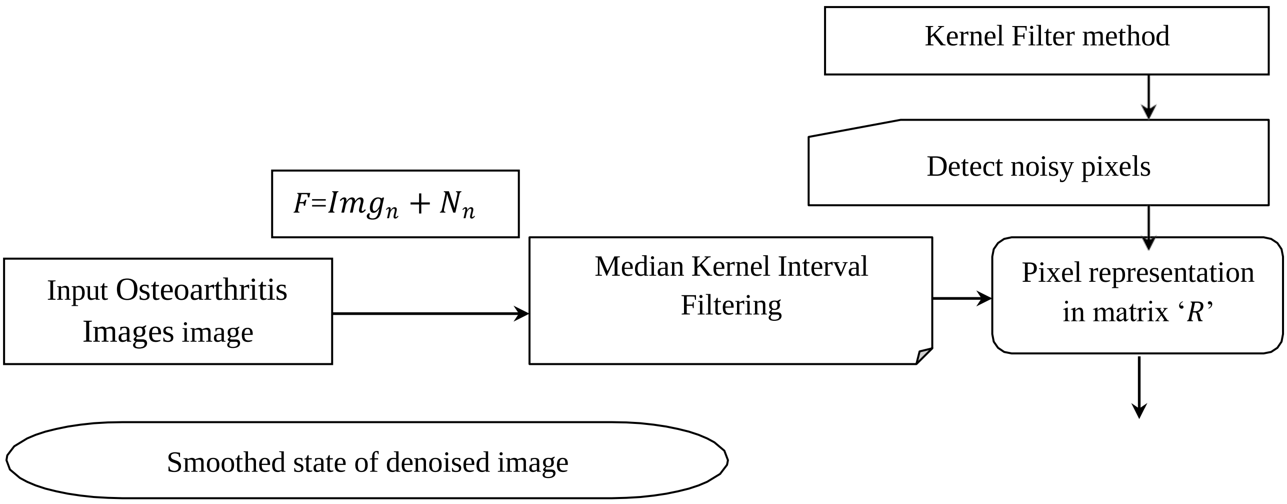


Figure 1 flow process of Median Kernel Interval Filtering

$F = Img_n + N_n$ .... Eqn (3.1)

Where, F denotes an input to the filter, Img_n indicates an input image and added with the some noisy 'N_n'. Each image has a number of pixels. A pixel is the minimum unit of a digital image and it is combined to form a total image. Therefore, these pixels are arranged into the matrix for simple computation and fast quality assessment. Each pixel is represented by means of a numerical value.

4. Multi-Wavelet Feature Extraction

The extraction of features from the kernel Filter image is significant before the image Wavelet and Signal process. In detail, various features are taken for image Wavelet Signal. The various features contain color and texture information from the kernel Filter images.

An improved Multi-Wavelet Feature Extraction (MWFE) is very simple and easy to process the Texture and Color Feature which work efficiently identifying the wavelet feature. It is employed to find the availability of the wavelet signal from the feature extracted pixel sensing. In this case, the texture and color wavelet identifies the pixel signals variation with a minimum number of iterations. Smooth wavelet data transmission without any image pixel loss. Algorithm 1 explains the step-by-step process of improved multi-wavelet feature extraction.

// Algorithm 1: improved Multi wavelet feature extraction
Input: Denoised Image
Output: Efficiently Extracted texture and color feature
1. **Begin**
2. **Initialize feature of** Subband '$S = s_1, s_2, \ldots, s_n$' (i.e. subband features) , inertia weightand learning factor
3. **For each** Sub band signal selection
4. Compute the fitness
5. **end for**
6. Calculate the pbest by comparing the present iteration with the previous iteration
7. Calculate the gbes**t** by comparin**g** pbest with the previous iteration and the lowest valueis gbes**t**
8. Update the Intensity and Mean features
9. Adjust the learning factor and the inertia weight with fitness values
10. **If** the maximum number of iterations is reached **then**
11. **O**ptimal solution is generated to find the new global best
12. **Else**
13. **Go to step 3End**

Algorithm 1 improved Multimodal Feature Extraction

4.Color Feature from Multi Wavelet signal Extraction

Color is significant visual information and it is established via content based image pixel signal. Thus, the color feature is first feature vector in wavelet. Color indicated by the first two moments such as the mean and the standard deviation.

$$C = \frac{1}{q\times p}\sum_{x=1}^{q}\sum_{y=1}^{p} M(x,y) \quad \text{.......Eqn (4.1)}$$

$$\sigma = \left(\frac{1}{q\times p}\sum_{x=1}^{q}\sum_{y=1}^{p}(M(x,y)-C)^2\right)^{\frac{1}{2}} \quad \text{..........................Eqn (4.2)}$$

From the above equations (4.1) and (4.2), mean 'C' and standard deviation 'σ' is computed. With the color moments, color histogram is used for detecting the image content. It is derived by,

$$H(i) = \frac{I_i}{p} \quad \text{.......Eqn (4.3)}$$

From the above equation (4.3), ‘I_i’ indicates the number of pixels of the i^th color and ‘p’ indicates the number of pixels in the image. These features are extracted and then stored in the database. For each block, all the features are determined and stored.

5 Texture and color Feature extraction from multi wavelet signal extraction

In the image Optimization and Classification process, texture is the next featureto be identified using Multi-Wavelet. The initial Wavelet coefficient in the Signal block indicates the energy information of the image whereas residual signal wavelet block components indicate the frequency information. The direction information is also provided in the block. The main directions with the gray level changes of the image areextracted and stored in the image database as referred as independent feature vectors. All sub block is independently processed and it is illustrated in figure 2

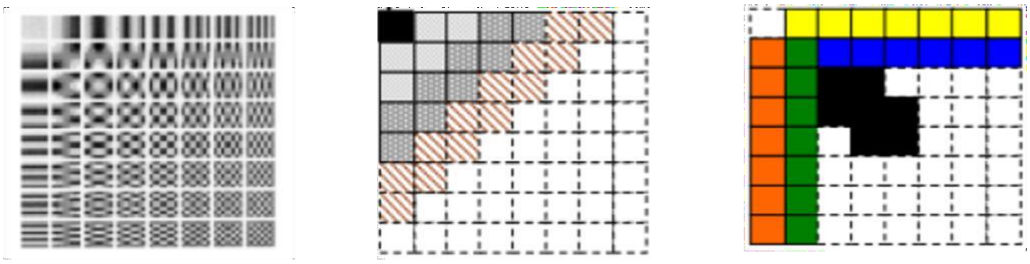
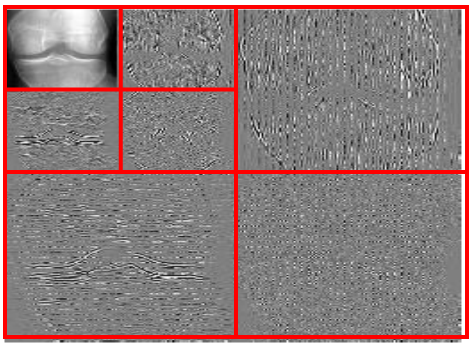


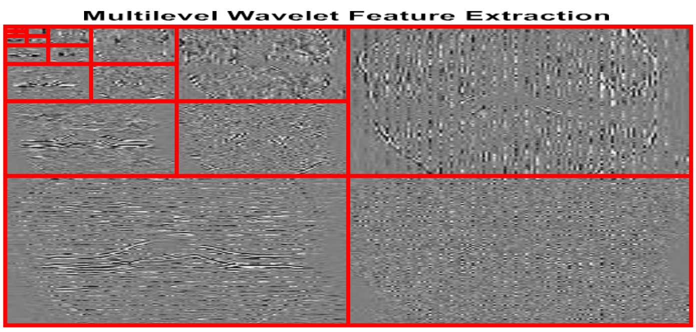
Figure 2 Multi-Wavelet Signal Process

Figure 2 shows the extraction of texture from Multi wavelet signal frequency blocks. As observed in the above figure, the horizontal and vertical information’s are obtained from each block and then processed for further purpose. After calculating all the values, mean and standard deviation over these values are determined and stored.

Feature vectors characterize the average greyness, horizontal texture, vertical texture and diagonal texture of a particular image sub block. These coefficients are purposely chosen and these are imperative to the greyness and image directionality. Moreover, low frequency coefficients of the sub block are only selected to provide maximum energy level in multi wavelet signal.

Multilevel Wavelet Feature Extraction





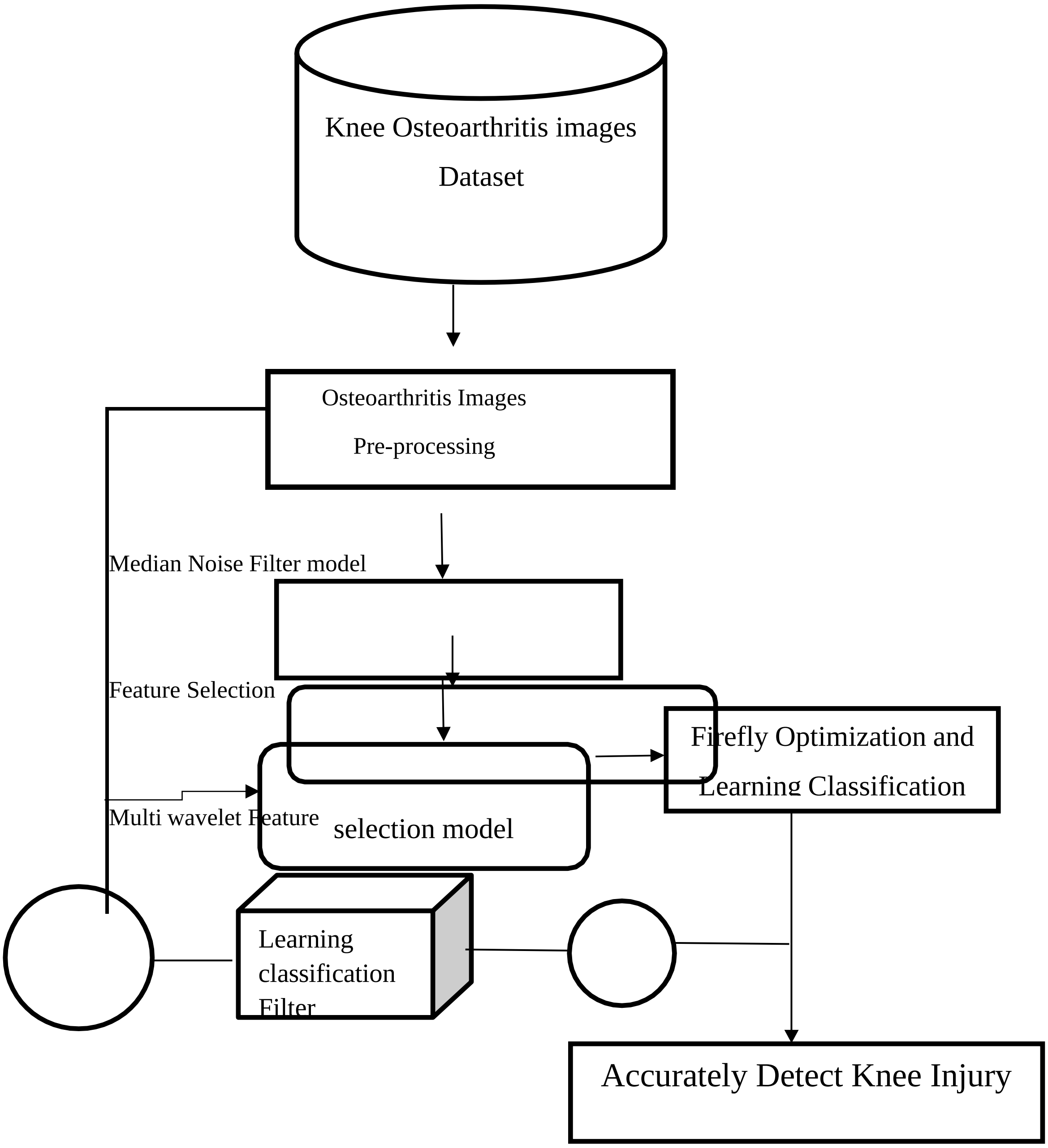
After obtaining or extracting the features, the features are extract from the intensity pixel . The similar process of feature extraction using wavelet is carried out for knee injury image. Then the similarity between the both the features i.e. trained features and features from knee injury image is compared. If the features are matched, same classes of knee injury feature extraction image.

3. Multimodal Artificial Bee Colony Firefly Optimization and Learning Classification :

The proposed algorithm consist of three different bees namely, employee bee that responsible to converse with other bees in exploiting the quality of optimization and classification. It delivers the information about the quality of classified image to the next bee.

The second bee is onlooker bee which makes a decision depending on the information providedby the employee bee. The third bee is scout bee observes the best quality of classified image based on the information given by the employee bee by using firefly algorithm. Algorithm 3 explains the firefly optimized based on learning classification.

Figure 3 : Architecture of median kernel and optimization and classification



(MMFOLC)

Algorithm 2 Wavelet feature Optimization

Input: Wavelet Feature Extraction images $I_{m(FeatExt)}$

Output: Optimized images $I_{m(opt)}$

Step 1. Begin

Step 2. **Initialize** the population $I_{m(rtrvd)}$, reflection U, visibility V, maximum numberof iteration i_{max}

Step 3. **Calculate** fitness for the population

Step 4. **Set** $i = 0$

Step 5. **While** $(i \leq i_{max})$

Step 6. **Evaluate** Normalization image feature

Step 7. **Update** U, V

Step 8. **Update** new solution by global search **Step 9.** **Evaluate** fitness of new solution S^{new}**Step 10.** **If** $(cfn < fn)$

Step 11. {

Step 12. Replace $S^{cur} = S^{new}$

Step 13. }

Step 14. **Else**

Step 15. {

Step 16. $S^{best} = S^{new}$

Step 17. }

Step 18. **End if**

Step 19. **Update** best solution

Step 20. **Calculate** average points of the best solution **Step 21.** **Calculate** fitness of the current the best solution**Step 22.** **Set** $i = i + 1$

Step 23. **End while**

Step 24. **Return** optimized image

Step 25. **End**

Algorithm 2 Describes the step-by-step process of Firefly Optimization Detection

Initially, population (Injury Detected images) generation is randomly carried outand it is represented as,

$$Kn_{m(rtrvd)} = \{Kn_1, Kn_2, Kn_3, \ldots \ldots, Kn_N\} \text{................................ Eqn (5.1)}$$

The Firefly optimization mutation 'P' is employed to increase the global searcharea as,

$$\mathsf{P} = \xi_g . \hbar_{I_{m(det)}} \text{.. Eqn (5.2)}$$

In (5.2), 'ξ_g' refers the Classifiction distribution, '$\hbar$' refers the position information of the weight values in the

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population. Thus, the new solution of the globalsearch space G^{new} is produced by,

$$G^{new} = P\,(U + V) \text{ .... Eqn (5.3)}$$

Where, 'U' refers the reflections and 'V' refers the visibility and formulated as

below.

$$U = \alpha * I_m 1[l].\,pts\,[b] \text{ .... Eqn (5.4)}$$

$$V = \beta * (B.\,pts\,[b] - I_m 1\,[l].\,pts\,[b]) \text{ .... Eqn (5.5)}$$

Where, '$I_m 1$' symbolizes the group of cells, '$pts\,[b]$' symbolizes the b^{th} point of l^{th} cell in $I_m 1$, '$B.\,pts\,[b]$' refers the best solution points, 'α, β' symbolizes the degree of reflection and visibility. Then, α, β are described as,

$$\alpha = \delta * (c_1 - c_2) + c_2 \text{ .... Eqn (5.6)}$$

$$\beta = \delta * (e_1 - e_2) + e_2 \text{ .... Eqn (5.7)}$$

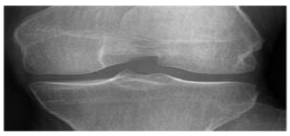
In equation (5.6) and (5.7), c_1, c_2, e_1, e_2 refers the constant values and 'δ' is therandom function. Then the fitness is computed depended on the feedback of the user for discovering the difference between the best solution and the current solution. The newsolution is produced as,

$$S^{new} = \begin{cases} S^{cur} & if\ (cfn < fn) \\ S^{best} & if\ (bfn < fi \end{cases} \text{ ......Eqn (5.8)}$$

In (5.8), S^{cur}, S^{best} refers the current solution and best solution, cfn, bfn refers the current fitness and best fitness. Then the new search area is formed by calculating the difference between the best solution and the average of the best point as follows,

$$U_b = \alpha * B.\,pts\,[b] \text{ .... Eqn (5.9)}$$

$$V_b = \beta * B.\,pts\,[b] - b_{avg} \text{ .... Eqn (5.10)}$$



Knee Osteoarthritis Image

Where, 'U_b' symbolizes the group of cells, '$pts\,[b]$' symbolizes the b^{th} point of l^{th} cell in V_b, '$B.\,pts\,[b]$' refers the best solution points, 'α, β' symbolizes the degreeof reflection and visibility

Where, 'b_{avg}' indicates the average value of the best points. After detecting thebest solution of knee injury detection,. This helps to increases the accuracy of knee injury detectio

Figure 4 : Architecture of Multimodal firefly Optimization and Learning Classification(MMFOLC)

// Algorithm 3:Firefly optimized Learning Classification

Input: Feature Extraction Image

Output: Classified knee injury detected Image

1. **Begin**

2. **Initialize Feature extract image**, maximum iteration ‘Maxiter’

3. **Employee bee** find the idle multi signal wavelet transformation

4. **Calculate** the fitness function value ‘f’

5. **If** $f(Curr_i) < f(fs_i)$ **then**

6. update previous position fs_i by current position $Curr_i$

7. **else**

8. place previous position fs_i

9. **end if**

10. Determine best optimal Detection

11. Stores the best Firefly optimization detection.

12. Scout bee sense the entire Classified image

13. $\boldsymbol{if}$ $(t = Maxiter)$ **then**

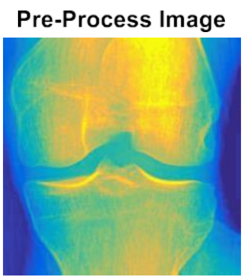
14. Select the best Classified image **else**

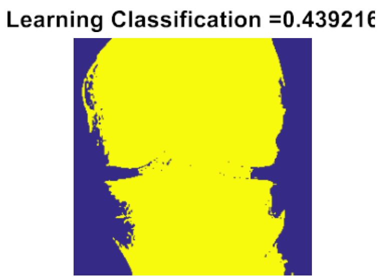
15. **t=t+1**

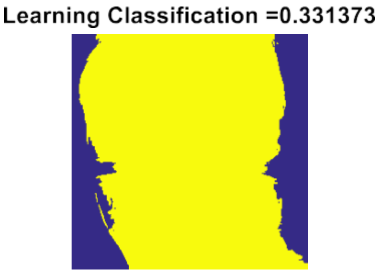
16. **go to step 4**

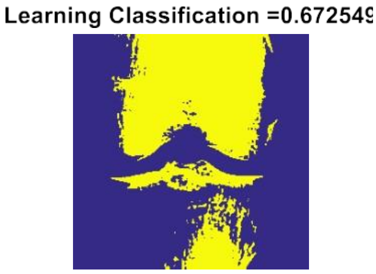
17. **End if18.**
End

Algorithm 3 describes the step-by-step process of a modified artificial bee colony withthe firefly algorithm to find the knee injury classification detection. The populations of a number of knee injury images are initialized randomly. For each image, the fitness is calculated. Then the current best machine is selected by applying the elitist selection strategy. If the algorithm reaches the maximum number of iterations, then the best optimal selection for handoff. Otherwise, go to Step 3. Finally, detect the knee injury detection area









6. Experimental settings

Experimental evaluation of proposed MMFOLC and existing MSRM [1] and Machine Learning- technique [2] is implemented in MATLAB using a Knee Osteoarthritis Dataset KL Grading–2018 dataset taken from https://www.kaggle.com/datasets/tommyngx/kneeoa.

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. 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, Severe.

7. Performance analysis

In this section, the quantitative analysis of the proposed MMFOLC and existing MSRM

[1] and Machine Learning- technique [2] are evaluated with various quantitative metrics such as Knee injury detection accuracy, false-positive rate, and knee injury detection time. These metrics are described in this section.

7.1 Knee injury detection accuracy: It is measured as the ratio of the number of images accurately detected as knee Osteoarthritis either normal or injury images to the total number of images taken as input. The formula for calculating the accuracy is given below,

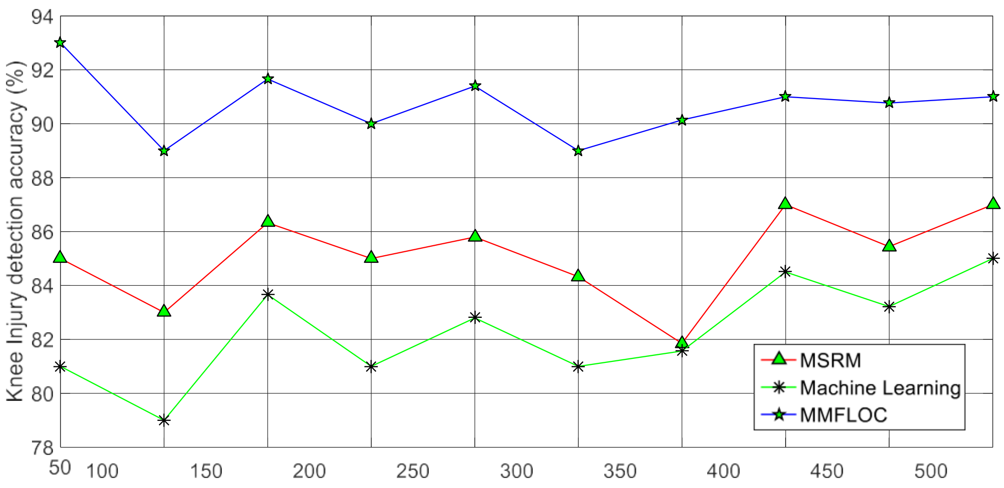
$$BTD_{acc} = \sum_{i=1}^{n} \frac{IAD}{I_i} * 100 \quad ......\text{Eqn (7.1)}$$

From the above equation (7.1), BTD_{acc} denotes knee injury detection accuracy 'I_{AD}' denotes an knee Osteoarthritis accurately detected either normal or injury, I_i denotes the number of images involved in simulation. Accuracy is measured in terms of percentage (%).

Table 1 Comparison of Knee injury Detection accuracy

Number of knee Osteoarthritis images	Knee Injury detection accuracy (%)		
	MSRM Model	Machine Learning	MMFOLC
50	85	81	93
100	83	79	89
150	86.33	83.66	91.66
200	85	81	90
250	85.8	82.8	91.4
300	84.33	81	89
350	81.85	81.57	90.14
400	87	84.5	91
450	85.44	83.22	90.77
500	87	85	91

Figure 3 : Architecture of median kernel and optimization and classification



Number of knee Osteoarthritis images (N)

The obtained result indicates that the brain tumor detection accuracy of the MMFLOC technique is higher than the other two existing methods. the knee injury detection accuracy is 92% and the detection accuracy of the existing MSRM Model [1] and Machine learning [2] are84% and 80% respectively

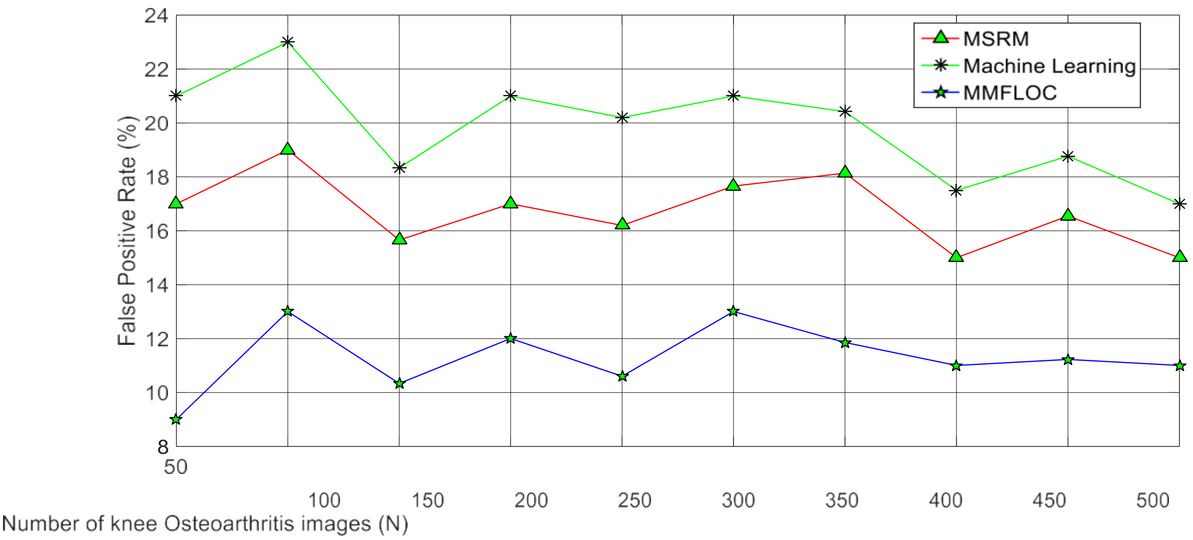
7.2 **False-positive rate**: It is measured as the ratio of a number of images incorrectly detected as either normal or injury images to the total number of images taken as input. The false-positive rate is measured as given below, R_{FP}

$$= \sum_{i=1}^{n} \frac{I_{ID}}{} * 100 \text{ ....Eqn (7.2)}$$

From the above equation (7.2), R_{FP} denotes false-positive rate, 'I_{ID} ' denotes an knee Osteoarthritis image incorrectly detected either normal or injury, I_i denotes the number of images involved in simulation. The false-positive rate is measured in terms of percentage (%).

Table 2 Comparison of false-positive rate

Number of knee Osteoarthritis images	False-positive rate (%)		
	MSRM Model	Machine Learning	MMFOLC
50	17	21	9
100	19	23	13
150	15.66	18.33	10.33
200	17	21	12
250	16.2	20.2	10.6
300	17.66	21	13
350	18.14	20.42	11.85
400	15	17.5	11
450	16.55	18.77	11.22
500	15	17	11



MSRM [1] and Machine Learning [2] and their false positive rates are 16% and 20%respectively. The above discussion proves that the proposed MMFLOC technique decreases incorrect detection.

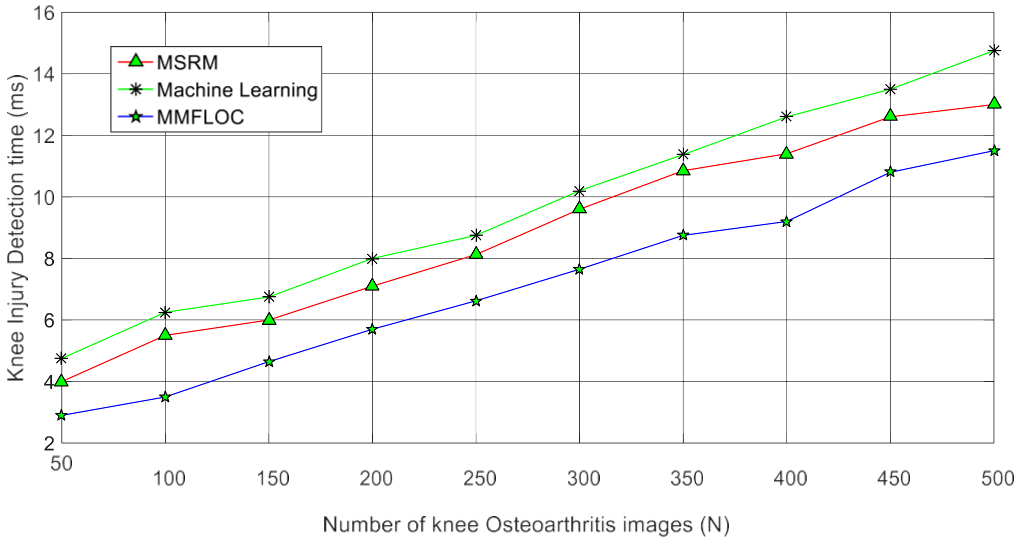
7.3 Knee injury detection time: It is defined as the amount of time consumed by thealgorithm to detect the injury as given below.

$$BTD_{time} = \sum_{i=1}^{n} I_i * Time\,[BTD] \text{ .... Eqn (7.3)}$$

From the above equation (7.3), the BTD_{time} denotes a knee Osteoarthritis injury detection time, I_i denotes the number of images, $Time\ [BTD]$ denotes a time consumed in knee injury detection. It is measured in terms of milliseconds (ms).

Table 3 Comparison of Knee injury detection time

Number of knee Osteoarthrit isimages	Knee Injury Detection time (ms)		
	MSRM Model	Machine Learning	MMFOLC
50	4	4.75	2.9
100	5.5	6.25	3.5
150	6	6.75	4.65
200	7.1	8	5.7
250	8.125	8.75	6.625
300	9.6	10.2	7.65
350	10.85	11.375	8.75
400	11.4	12.6	9.2
450	12.6	13.5	10.8
500	13	14.75	11.5



the proposed technique consumes 2.9ms for identifying the tumor. Whereas 4ms and 4.75ms are consumed by the MSRM Model [1] and Machine Learning [2] for detecting the Knee injury. From the estimated results, it is cleared that the brain tumor detection time using the proposed MMFLOC technique is lesser when compared to other existing methods.

6. CONCLUSION

A knee Osteoarthritis images detection algorithm is developed in this research for identifying the injury detection from the Osteoarthritis images by proposing the MMFLOC technique. Initially, the input knee Osteoarthritis images are subjected to pre-processing for Median Kernel filter . Then, the obtained preprocessed images are multi wavelet feature extraction . Then the output of wavelet feature extraction images is given to the input of the firefly optimization for subband multi wavelet the input images to minimize the knee injury detection time. Followed by, multiple features such as texture, color, shape, intensity are extracted to identify the knee injury. At last, the Learning classification is applied to estimate the classified features with the testing injury features. The analysis results are used to identify the knee injury with higher accuracy and lesser time. The comprehensive experimental evaluation is carried out with an knee Osteoarthritis database. The qualitative and quantitative results discussion shows that the MMFLOC technique has received better performance in terms of achieving higher Knee injury detection accuracy and lesser time consumption and false- positive rate than the other related works.

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