Methodology for the analysis and detection of knee abnormality using Vibroarthrographic signals

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by

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CERTIFICATE

This is to certify that the work contained in this project report entitled **" Methodology for the analysis and detection of knee abnormality using Vibroarthrographic signal"** submitted by **ABHISHEK SINGH** (**Roll No: 20MECP01**) to PDPM-Indian Institute of Information Technology, Design and Manufacturing, Jabalpur towards partial requirement of **Master of Technology** in Electronics and Communication has been carried out by him under my supervision and that it has not been submitted elsewhere for the award of any degree.

Jabalpur - 482005 | Dr. Varun Bajaj

——— | Thesis Supervisor

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Jabalpur - 482005 **Abhishek Singh**

ABSTRACT

Vibroaurthrography (VAG) is a technique to detect knee joint defects. VAG signals are collected from the human knee joint by placing electrodes on the knee. VAG signals contain information about the working status of muscles. This thesis aims to develop new methods for the analysis and classification of VAG signals. The detail of these methods and features employed for detection are summarized as follows:

The knee joint is the most intricate in the human body. This joint faces immense reaction forces during daily routine work that may vary around three to seven times the body weight. These high reaction forces may convert small malfunctioning into severe conditions and can be avoided by early detection of knee health conditions. Vibroarthrography (VAG) is the most emerging tool to detect knee joint abnormalities. In this paper, an application of the empirical mode decomposition (EMD) is presented to discriminate between normal and abnormal knee joint VAG signals. EMD is employed to disintegrate input VAG signals into several intrinsic mode functions (IMFs). Twelve different non-linear, entropy, and shape-based features are elicited from each IMF provided by EMD. Kruskal-Wallis (K-W) test is employed to identify the best suitable features to discriminate between normal and knee-joint affected VAG signals. The simulation results with the publicly available VAG database are included to show the effectiveness of the presented study.

In another work, grey-wolf-optimization (GWO) is integrated with tunable Q wavelet transform (TQWT) to obtain the optimized decomposition parameter for efficient screening of knee joint abnormalities using VAG signals. Non-stationary VAG signals are decomposed into stationary compo-

nents using the optimized TQWT method. Several entropy-based and shape-based features have been extracted from the sub-bands. Evaluated features are selected using the K-W test and given to different classifiers to get higher performance. The highest classification accuracy of 90.8 percent is achieved using the support vector machine (SVM) classifier.

Contents

List of Figures

List of Tables

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Chapter 1

INTRODUCTION

Biomedical signals are the collection of pathological and physiological activities of tissues, neurons, genes, etc. They are the collection of electrical and non-electrical activity of the human body. These signals have time-varying property. Electrical biomedical signals are the representation of electrical potential differences across specific organs. Electrocardiogram (ECG), Vibroarthrogram (VAG), Electroencephalogram (EEG), etc are the different types of biomedical signals. Any disturbance in the biological system results in the variation of physiological processes, which affects the working and general health of the system. Signals in the case of the orthographic process differ from normal signals. Proper and adequate analysis of these signals may give the adequate information about the status of the human respiratory system. The task of accessing the information from the signals becomes tough as the signal goes complex. VAG signals are used to analyze the condition of human knee disorder; this thesis proposes various techniques for the analysis of VAG data in different biomedical and health care applications.

1.1 Vibroarthrography (VAG)

Vibroarthrography (VAG) is the study of the human knee joint, with the help of VAG signal which is generated due to friction between the femur, tibia, and patella caused by the movement of the human leg. VAG signal produced from the human knee is non-stationary in nature because the friction between the patella and tibia is non-uniform in nature, so on movement, it produces non-stationary signals.

1.1.1 Acquisition of VAG signals

To obtain VAG signals, the subject has to be set over a horizontal bench with hanging legs. Then electrodes have to be connected across the knee. After that as per instruction, the subject has to swing his leg from zero degree position to one hundred forty-degree positions, and then back from one hundred forty to zero degree back, and the time taken in all this process is 4 Sec. The position of zero degrees is known as flexion and the position of one hundred forty degrees is known as extension.

1.1.2 Application of VAG signals

- Vibroarthrographic signal helps us to understand the health condition of the knee joint, which symbolizes the level of friction present between the patella, tibia, and femur. As the roughness of the surface increases the spikes would be shown in the VAG signal. This can be used in the early detection of human knee abnormalities.
- Vibroarthrographic signal use to calibrate the Exo-skeleton robotic system, which helps the aged subject to move easily. It is useful, especially for the development of the lower body exoskeletal system.

1.2 Literature Survey

In the literature, various researchers proposed different computer-aided discrimination systems to differentiate between normal and abnormal (knee-joint affected) VAG signals. For example, authors in [42] utilized the wavelet decomposition method to decompose VAG signals into several wavelet coefficients. For the categorization of normal and pathological VAG signals, Ranggayyan and Wu [32] derived several entropy-based characteristics. In another study, the same group [31] extracted fractal dimension-based features from the VAG signals. Time-frequency distribution (TFD) of input VAG signal has been scrutinized using double-density dual-tree complex wavelet transform (DTCWT) by Sharma *et al.* [37]. The short-time Fourier transform (STFT) approach has been employed to compute statistical features from VAG signals by Mrunal *et al.* [39]. For reliable identification of knee joint methodologies with minimal time, a new approach is introduced in [29]. TQWT has been introduced to deconstruct the VAG signals into sub-band signals, and entropy information is retrieved from each subband by Mascarenhas *et al.* in [21]. Various other machine learning-based approaches are described in the literature. The selection of more appropriate features for a machine learning classifier is difficult and time-consuming. Therefore, this study presents automated discrimination of normal and knee joint-affected VAG Signals by utilizing empirical mode decomposition (EMD) and the Kruskal Wallis (KW) test. EMD is applied to disintegrate VAG signals into several intrinsic mode functions (IMFs). Twelve different non-linear, entropy and shape-based features are elicited from the IMFs. Kruskal-Wallis (K-W) test is used to discriminate the best suitable features to identify normal and knee joint-affected VAG signals.

1.3 Motivation

- Knee joint abnormalities can take serious faces, but can be avoided if detected in the early stage.
- According to WHO statics, symptomatic osteoarthritis affects 9.6% of males and 18.0% of women in the world [37].
- In case of severe knee complications, the patient needs to go for a knee replacement, which is an invasive technique that includes the removal of dented and worn out surface of the knee joint [37].

- Various traditional techniques like computer tomography (CT), X-Ray imaging, and magnetic resonance imaging (MRI), are available for the screening of knee-related abnormalities, but these traditional techniques are unable to identify the minute changes that come in the early stage [18].

1.4 Objective of work

This thesis aims to find some new features and methodology for the analysis and classification of VAG signals. Various aims of this thesis are

- Analysis of non-stationary signal VAG to diagnose the human knee joint.
- Development of a non-invasive and easy method for the early detection of knee joint abnormalities.
- To analyze the normal and abnormal VAG signal using the intrinsic mode of functions generated by the EMD algorithm.
- To improve the VAG signal classification adaptive TQWT has been used to analyze.

1.5 List of publications

1. Knee Joint VAG Signals Using EMD"ICCWC-2022 (Accepted with best paper award)Abhishek Singh, Kapil Gupta, Varun Bajaj " Discrimination of Normal and Abnormal

2. Abhishek Singh, Varun Bajaj "Application of Adaptive Tunable Q Wavelet Transform to VAG Signal for Automated Detection Knee Joint Abnormalities."(Under preparation)

1.6 Organization of thesis

Chapter 1 Present the introduction section including the literature survey, while the other parts of the thesis are arranged as follows

Chapter 2 Present a method for the Discrimination of Normal and Abnormal Knee Joint VAG Signals Using EMD. The method is arranged in the subsection of introduction, methodology, dataset, result, and discussion.

Chapter 3 Application of Optimised Adaptive Tunable Q Wavelet Transform to VAG Signal for Automated Detection Knee Joint Abnormalities. A method is arranged in a subsection of introduction, methodology, dataset, result, and discussion.

Chapter 4 Present the conclusion and the future scope of this work.

Chapter 2

Analysis of Abnormalities in Knee Joint VAG Signals Using EMD

2.1 Methodology

The layered diagram of the presented system is shown in Fig. 1.

2.1.1 Dataset

A publicly available VAG database is employed to validate this study. This obtained from 51 normal and 38 abnormal volunteers [30]. To record the VAG signal each volunteer was said to sit on a bench, and an accelerometer setup

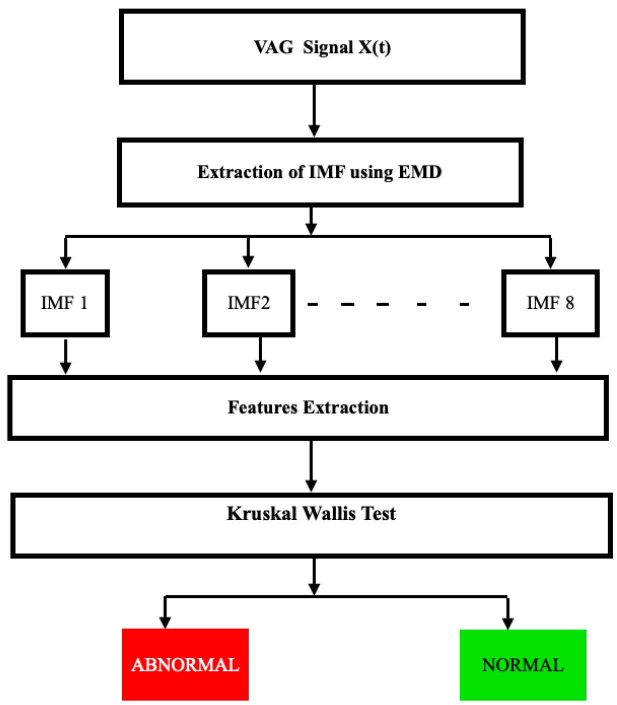

Figure 2.1: Layered diagram of the presented system.

was utilized to acquire VAG signals. The volunteers were told to swing their leg from extension to flexion and back to an extension, which means from zero degrees to one hundred forty degrees and back to zero degrees again, such that the movement process completes in $4 - sec$ [33]. The data set is recorded with a sampling frequency of 2KHz. Before digitizing the signal, it was filtered and amplified. This process had been done in the laboratory of the University of Calgary, Canada. The details of the data can be found in [30]. VAG signals of normal and unhealthy subjects are represented in Figure 3.1.

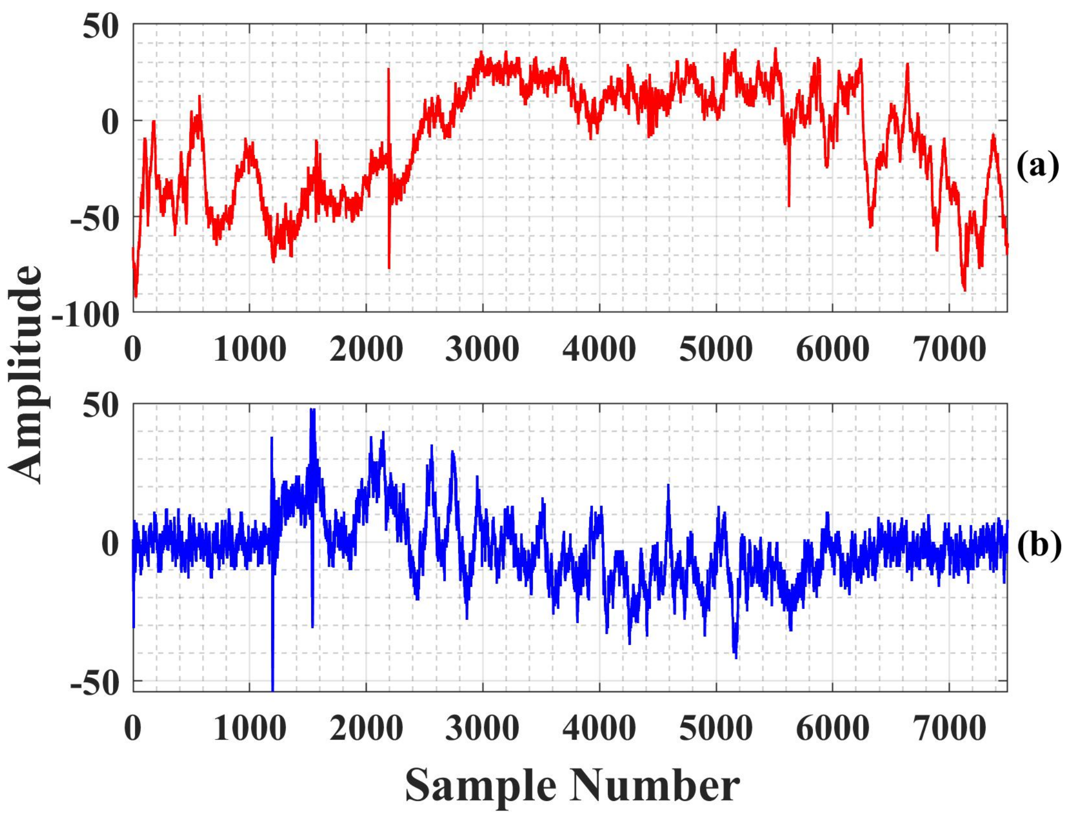

Figure 2.2: Typical VAG signals of (a) Abnormal (b) Normal subject

2.1.2 Empirical Mode Decomposition (EMD)

EMD is a data-dependable and adaptable approach. The EMD method does not involve any prerequisites about the signal's stationarity or linearity. The essence of the EMD is to decompose non linear time varying VAG signals $z(t)$ into various intrinsic mode functions (IMFs) [5, 27]. Each IMFs must have to satisfy the following criteria: 1) the total of maxima or minima and the number of zero crossings should be the same or differ by no more than one. 2) the average scores of the envelope formed by the local maxima and the envelope provided by the local minima are zero at any moment in time.

The procedure of EMD method for a input VAG signal $z(t)$ can be summed up as follows [5]:

1. Identify maxima and minima (extrema) of the input VAG signal $z(t)$.
2. With the help of cubic line interpolation connect the local maxima and local minima to obtain upper and lower envelope $V_u(t)$ and $V_l(t)$ respectively.
3. Estimate the local mean as $m_e(t)$

$$[m_e(t) = [V_u(t) + V_l(t)]/2] \tag{2.1}$$

4. Extracts the details.

$$h_1(t) = z(t) - m_e(t) \tag{2.2}$$

5. Decide whether $h_1(t)$ belongs to IMF, with the help of previously discussed two conditions.

6. Repeat the process from 1 to 4 until the first IMF is obtained.

As first IMF is extracted, interpret $p_1(t) = h_1(t)$, is the lower temporal scale in $z(t)$. To obtain the remaining IMFs, produce residue $r_1(t) = z(t) - p_1(t)$, which is processed as a new signal. Repeat all the steps over the new signal until the final residue is obtained in the form of nearly constant or from which no more IMFs can be evoked. The input VAG signal $z(t)$ can be symbolized at the end of the decomposition.

$$z(t) = \sum_{n=1}^{N} p_n(t) + res_N(t) \tag{2.3}$$

where, N represents the total generated IMFs, $p_n(t)$ represents the n^{th} IMF, and $res_N(t)$ denotes the residue term. Each IMF obtained from Eq. 2.3 is posses of consequential local frequency, different IMFs never possess the same frequency at the same time. The IMFs obtained from decomposition of normal and problematic VAG signals are shown in Fig. 2.3.

2.1.3 Features extraction

To analyze the graphical variation of each IMF, and to discriminate between normal and abnormal VAG signals. We have extracted twelve different features, defined as follows [6]:

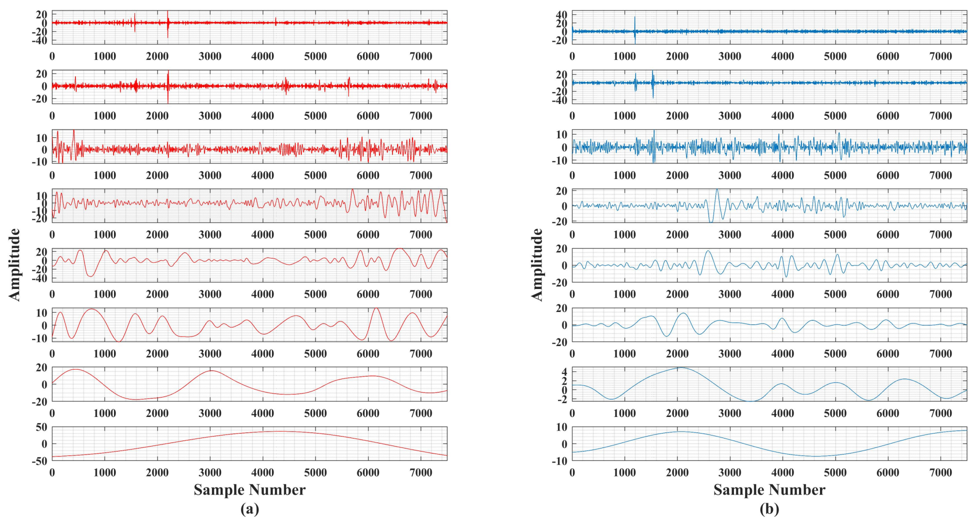

Figure 2.3: Imfs of (a) Abnormal (b) Normal knee joint VAG signal

- **Mean (M):-** The mean is the average value of dataset. Computed as

$$mean = \frac{1}{n} \sum_{i=1}^{(N-1)} x_i \tag{2.4}$$

- **Root Mean Square (RMS):-** It is also known as quadratic mean and is termed as the square root of the mean square. It is expressed as,

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} {x_i}^2} \tag{2.5}$$

- **Standard Deviation (σ) :-** It is the estimation of variations of a set values. Higher the value of σ indicates values spread over a wider range and value close to mean for lower value of σ. This is expressed as,

$$\sigma = \sqrt{\frac{1}{(n-1)} \times \sum_{i=1}^{n} (x_i - x_m)^2} \tag{2.6}$$

- **Shanon Entropy (ShanEn) :-** It is the average amount of information in x. It is given as

$$S_{ShanEn}(x) = -\sum_{j=0}^{(K-1)} (k_j(x))^2 (log_2(k_j(x)))^2 \tag{2.7}$$

- **Log Energy Entropy (LogEn) :-** The expression of LogEn is given as,

$$S_{LogEn}(x) = -\sum_{j=0}^{(K-1)} (log_2(k_j(x)))^2 \tag{2.8}$$

  The more regularity in the VAG signal will result in a lesser value of entropy.

- **Threshold Entropy (TE) :-** Threshold entropy is a method of selecting an optimal threshold value for a signal by selecting the data intensity from a signal histogram that has the highest entropy of the total signal.

- **Sure Entropy (SE) :-** It is based on Stein's unbiased risk estimator. It's a technique for measuring aspects of information to accurately describe a signal.

- **Norm Entropy (NE) :-** It is evaluated as

$$\frac{\sum_{i,j=1}^{N} |t(i,j)|^p}{N} \tag{2.9}$$

where p indicates the power and it must reside in the range of 1 to 2.

- **Permutation Entropy (PE) :-** Permutation Entropy is an adaptable time-series technique that provides a quantifiable quantification of the complexity of a dynamic system.

- **Skewness (Sk) :-** The term skewness deals with the symmetry of distribution heaviness of the distribution of the tail. Expression for the evaluation of Sk is given by

$$S_k = (Mean - Mode)/StandardDeviation \tag{2.10}$$

- **Kurtosis (K) :-** Kurtosis gives facts about the flatness of the curve. The expression of kurtosis is given as

$$\beta_2 = \mu_4/\mu_2^2 \tag{2.11}$$

where, β_2 belongs to Kurtosis, μ_4 belongs to the fourth central moment, μ_2 belongs to the second central moment of distribution.

- **Simple squared integral (SSI) :-** It expresses the energy contain of

VAG signals. It is given as, [14].

$$SSI = \sum_{i=1}^{n} (|x_i^2|) \tag{2.12}$$

2.1.4 Kruskal-Walis (K-W) Test

The K-W test more generalized form of the two-class Wilcoxon rank test and one-way analysis of variance (ANOVA) test. ANOVA is a parametric test that can be applied to a normally distributed continuous variable. Whereas, the K-W test is a non-parametric statistical test, that compares the contretemps between two or more distinguishable sampled classes on a single, infrequently dispersed continuous variable. K-W test is commonly used to determine when two or more classes vary on a single variable that fails to meet the uniformity constraints of ANOVA [22].

2.2 Results And Discussion

The selection of the most suitable feature to discriminate between normal and abnormal VAG signals is a time-consuming task. Therefore, in this work input, the VAG signal is disintegrated into several IMFs by applying the EMD algorithm. Twelve different entropy-based and statistical features are evaluated from each IMF. K-W test is used to discriminate the most suitable feature. The probabilistic values for entropy-based features are depicted in Table 1. It is obvious from the Table 1, all entropy-based features are suitable

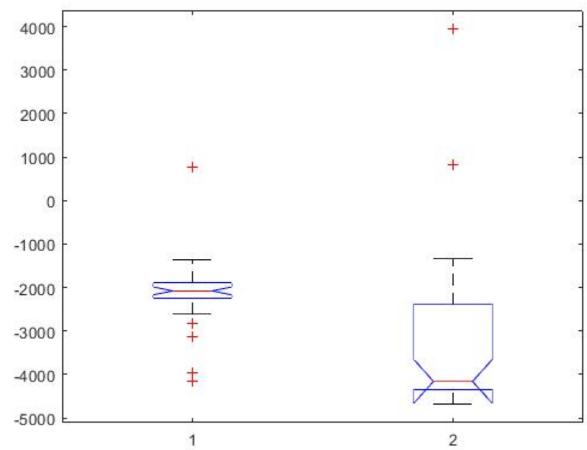

Figure 2.4: KW TEST (LOG ENERGY ENTROPY).

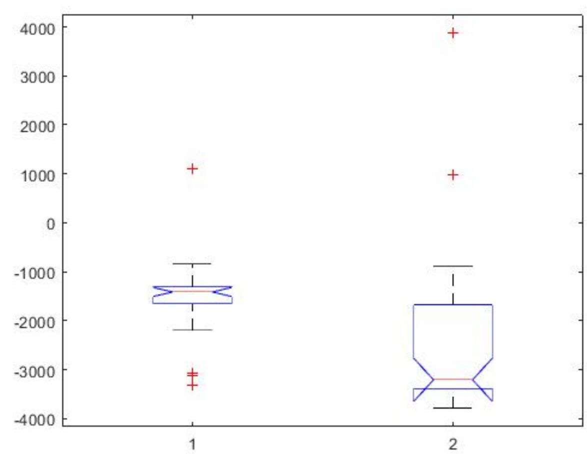

Figure 2.5: KW TEST (SURE ENTROPY).

Table 2.1: Probabilistic values for entropy-based features

Imf No.	ShanEn	LogEn	NE	TE	PE	SrE
Imf-1	0.0065	$2 \times 10^{(-5)}$	0.0002	0.0002	0.0449	$1.28 \times 10^{(-5)}$
Imf-2	0.0573	0.0472	0.0377	0.0001	0.7553	0.0407
Imf-3	0.868	0.2531	0.7084	0.0039	0.4001	0.2531
Imf-4	0.4298	0.5061	0.3136	0.4703	0.0018	0.3943
Imf-5	0.4671	0.2707	0.3237	0.0428	0.0016	0.1735
Imf-6	0.9255	0.8926	0.9503	0.3448	0.2619	0.9255
Imf-7	0.7711	0.868	0.9669	0.8762	0.7474	0.9388
Imf-8	0.9751	0.5962	0.8031	0.589	0.7632	0.8926

for IMF-1. NE, TE, and SrE are suitable for IMF-2. Only TE is suitable for IMF-3. Only PE is suitable for IMF-4. PE and TE are suitable for IMF-5. No any entropy-based features are appropriate for the rest of the IMFs.

The probabilistic values for statistical-based features are mentioned in Table 2. It can be perceive from Table 2, that RMS, STD, SSI, and IVAG are

Table 2.2: Probabilistic values for statistical-based features

Imf No.	M	RMS	STD	Sk	K	SSI
Imf-1	0.28	0.0034	0.0034	0.4735	0.1941	0.004
Imf-2	0.5962	0.0496	0.0496	0.6327	0.3829	0.0521
Imf-3	0.1096	0.0981	0.0891	0.693	0.2619	0.9917
Imf-4	0.4059	0.4059	0.4059	0.5061	0.1836	0.3885
Imf-5	0.1941	0.4545	0.4482	0.0097	0.0865	0.442
Imf-6	0.6551	0.9586	0.9669	0.4735	0.6035	0.9751
Imf-7	0.3186	0.8598	0.8762	0.7791	0.6254	0.8031
Imf-8	0.0276	0.8597	0.8598	0.884	0.1487	0.868

suitable for IMF-1. RMS, STD, and IVAG are suitable for IMF-2. Mean is suitable for IMF-8. No, statistical-based features are suitable for the rest of the IMFs. This study has been simulated over the system having an Intel processor, 16GB RAM, and 1TB hard drive, with the help of MATLAB software.

2.3 Summary

In this study, an application of EMD is explored to differentiate between normal and abnormal VAG Signals. EMD is a non-stationary signal processing technique that has been used for decomposing VAG signals into multiple IMFs. Twelve different features are elicited from each IMF. To find the most relevant features, a non-parametric K-W test is applied. It is concluded from this study that entropy-based features are most suitable to distinguish between normal and knee joint-affected VAG signals.

Chapter 3

Application of Adaptive TQWT for Detection of Knee-Joint Abnormalities Using VAG Signals.

3.1 Methodology

3.1.1 Adaptive tuneable Q wavelet transform (ATQWT)

TQWT is widely utilized in the biomedical data processing. In terms of the tuneable Q factor, it differs from standard WT. The generation one low pass SB (LPS) and multiple high pass SBs (HPS) are produced as a result of the input signal's decomposition by TQWT. The decomposition boundaries namely, oversampling rate (r), number of levels (J), and quality factor (Q), are needed to disintegrate the VAG signals into SBs by TQWT. The recognition of abnormalities in the knee with the help of the VAG signal by TQWT needed an empirical selection of decomposition boundaries. To obtain the optimized decomposition parameters a GWO algorithm is added with the TQWT method. The term "oversampling rate" (r) refers to a sampling procedure that uses a sampling rate that is larger than or equal to the Nyquist rate to sample an input signal. if, $S_0^J(\omega)$ is LPS and S_1^J depicts the HPS.

(ϕ) is a low pass scaling factor and (ζ) gives the high pass scaling factor. Their relation with Q is given as,

$$\zeta = \frac{2}{(1+Q)} \tag{3.1}$$

For a temporal domain response with good localization, an oversampling rate of more than or equal to 3 is preferred. The value of r controls the LPS ϕ. Their relation can be given as

$$\phi = 1 - \frac{\zeta}{r} \tag{3.2}$$

J_{max} gives the maximum number of decomposition level, and mathematically it is depicted as

$$J_{max} = floor(\frac{log\frac{K}{4+(1+Q)}}{log\frac{(1+Q)}{(1+Q-\frac{2}{r})}}) \tag{3.3}$$

Equation (3) and (4) indicates that the tuning parameter (Q, r) can control the LPS and HPS response. Effective decomposition and well-localized response depend on the real values of Q and r. Input VAG fragments can be decomposed into J number of SBs are represented as

$$S(t) = S_a(t) + e_d s(t) \tag{3.4}$$

where, decomposition error is given by $e_d s(t)$. Input VAG fragment is given by $S(t).S_a(t)$ shows an approximated signal. Low-pass and high-pass scaling, the discrete Fourier transform (DFT), and filter banks analysis are used to produce the SBs.

To minimize the $e_d s(t)$, manual selection of Q and r is tedious and an experimental task.

To eliminate these constraints, the GWO optimization algorithm is employed to get better reconstructed VAG signals with minimum error. The reconstruction and decomposition of any VAG fragment is depend on the selction of LPS and HPS. Moreover, Q and r controls the value of LPS and HPS. The objective function to minimize the MSE is given,

$$x_e ds(t) = \int_0^{+\infty} (S(t)) - S_a(t))^2 dt \tag{3.5}$$

Many optimization methods are investigated to provide the better solution of a problem. Gray-Wolf optimization (GWO) method is one of such technique that gives fast convergence and more accurate solution for a problem. (α):alpha wolves gives best solution, (β): beta wolves is second best solution, and delta(δ) wolves: is worst solution. Mathematically expressed as

$$\overrightarrow{F} = \overrightarrow{C}.\overrightarrow{Q,r} \tag{3.6}$$

$\vec{C}$ is vector coefficient and number of iterations are given by n. $\vec{Q,}r_p$: Position vector of prey and $\vec{Q,}r$: number of gray wolf. The coefficient vectors are computed as

$$\overrightarrow{A_1} = 2.\overrightarrow{q}_2\overrightarrow{B_1} = 2.\overrightarrow{a.q_1} - \overrightarrow{a} \tag{3.7}$$

where, $\overrightarrow{q_1}$ and $\overrightarrow{q_2}$ are the random vectors, ranges in between 0,1. After encircling the prey, the next stage is to assault it. Alpha, beta, and delta wolves start the hunt for the prey. The hunting mechanism equation can be expressed as

$$\begin{aligned}
&\overrightarrow{F_\alpha = |\overrightarrow{C}|.} \\
&\overrightarrow{Q.r}_\alpha - \overrightarrow{Q.r}_1| \\
&\overrightarrow{F_\beta} = |\overrightarrow{A}..r \quad {}_\alpha - \overrightarrow{Q.r}_1| \\
&\overrightarrow{F_\delta} = |\overrightarrow{A}.\overrightarrow{Q.r}_\alpha - \overrightarrow{Q.r}_1| \\
&\overrightarrow{Q,r}_= |\overrightarrow{Q,r}_\alpha \ \overrightarrow{B,F_\alpha}|
\end{aligned} \tag{3.8}$$

where the optimum position vectors for the wolves *alpha*, *beta*, and *delta* are $(\overrightarrow{Q}_.\overrightarrow{r}_.)_p$, $(\overrightarrow{Q}_{.},\vec{r}_.)_s$, and $(\overrightarrow{Q},\overrightarrow{r})_3$.

The function of "." is element-wise dot multiplication. The *alpha* wolves, who supply the ideal amount of $Q_.$ and $r_.$, offer the fittest solution. For both normal and abnormal various values of J_{max} are obtained from each VAG signal. To obtain the similarity between normal and abnormal VAG signals the optimum value of J_{opt} is obtained. $Jopt$ is the mean of the maximum decomposition level J_{max} of both normal and abnormal VAG signals, expressed as follows:

$$J_{opt} = floor(\frac{1}{K}\sum_{i=1}^{I}(\frac{1}{N}(\sum_{n=1}^{N} J_{max}^{kc}))) \tag{3.9}$$

where K indicates the number of signals from each state of conditions (normal and abnormal) and C signifies the conditional states.

3.1.2 Features Extraction

To analyze the graphical variation of each IMF, and to discriminate between normal and abnormal VAG signals. We have extracted twelve different features, they are expressed as follows: [6]:

- **Mean (M):-** The mean is the average value of dataset. Computed as

$$mean = \frac{1}{n}\sum_{i=1}^{(N-1)} x_i \tag{3.10}$$

- **Root Mean Square (RMS):-** It is also known as quadratic mean and is termed as the square root of the mean square. It is expressed as,

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- **Standard Deviation (σ) :-** It is the estimation of variations of a set values. Higher the value of σ indicates values spread over a wider range and value close to mean for lower value of σ. This is expressed as,

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- **Shanon Entropy (ShanEn) :-** It is the average amount of information in x. It is given as

$$S_{ShanEn}(x) = -\sum_{j=0}^{(K-1)} (k_j(x))^2 (log_2(k_j(x)))^2 \tag{3.13}$$

- **Log Energy Entropy (LogEn) :-** The expression of LogEn is given as,

$$S_{LogEn}(x) = -\sum_{j=0}^{(K-1)} (log_2(k_j(x)))^2 \tag{3.14}$$

  The more regularity in the VAG signal will result in a lesser value of entropy.

- **Threshold Entropy (TE) :-** Entropy thresholding is a method of selecting an optimal threshold value for a signal by selecting the data intensity from a signal histogram that has the highest entropy of the total signal.

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$$\beta_2 = \mu_4/\mu_2^2 \tag{3.17}$$

where, β_2 belongs to Kurtosis, μ_4 belongs to the fourth central moment, μ_2 belongs to the second central moment of distribution.

- **Simple squared integral (SSI) :-** It expresses the energy contain of

VAG signals. It is given as, [14].

$$SSI = \sum_{i=1}^{n} (|x_i^2|) \tag{3.18}$$

3.2 Result and Discussion

3.2.1 Kruskal-Walis (K-W) Test

The K-W test more generalized form of the two-class Wilcoxon rank test and one-way analysis of variance (ANOVA) test. ANOVA is a parametric test that can be applied to a normally distributed continuous variable. Whereas, the K-W test is a non-parametric statistical test, that compares the contretemps between two or more distinguishable sampled classes on a single, infrequently dispersed continuous variable. K-W test is commonly used to determine when two or more classes vary on a single variable that fails to meet the uniformity constraints of ANOVA [22].

3.2.2 Classifier

The goal of this section is to opt for the most suitable machine learning classification algorithm for the detection of abnormal VAG signals more efficiently. The various variant of classifiers algorithm namely logistic regression(LR), support vector machine(SVM), decision tree(DT), Gaussian SVM (FG-SVM), ensemble boosted tree (EBT), and extreme learning machine

(ELM), and Naive Bayes classifier (NBC) are explored. LR uses a non-linear relationship with the help of a sigmoid activation function to classify two classes [11]. FGSVM offers fast classification and medium memory use and can classify binary, as well as multi-class [44]. NBC [35], is a combination of classification techniques based on the Bayes theorem. The DT classifier algorithm chooses a tree-like design to make the selection between two groups, which is based on human behavior interpolation [28]. Weighted KNN is a well-organized classifier that utilizes the sum of weights of related classes, where the element assigned to the class that has the highest sum of the weights in between the target classes [47]. SVM is one of the powerful and famous supervised learning algorithms. The SVM can design the best line or decision boundary, that can segregate the data into categories. SVM chooses the extreme vectors from the hyperplane, which is further used for the creation of decision boundary [10]. This classifier gives the highest rate of accuracy in the classification of VAG signals into normal and abnormal categories, which is 90.9 percent with hold-out validation of 9 percent. The performance of the developed method has been computed by calculating seven matrices namely, Specificity, Accuracy, F-1 score, Sensitivity, False Alarm Rate, Receiver operating characteristic(ROC), and Precision. The confusion matrix and ROC graph are depicted in Fig.3.5 and Fig.3.4 respectively.

$$Specificity = \frac{T_N}{T_N + F_P} * 100 \tag{3.19}$$

$$Accuracy = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} * 100 \tag{3.20}$$

$$F - 1Score = \frac{2T_P}{2T_P + F_P + F_N} \tag{3.21}$$

$$Sensitivity = \frac{T_P}{T_P + F_N} * 100 \tag{3.22}$$

$$FalseAlarmRate = \frac{F_P}{F_P + T_N} * 100 \tag{3.23}$$

$$Precision = \frac{T_P}{T_P + F_P} * 100 \tag{3.24}$$

where, T_P-True positive events; F_P- False positive; T_N-True Negative; F_N-False Negative The evaluation Characteristics obtained are given in the table 3.1

Table 3.1: Evaluation Characteristics

Parameters	Results (in %)
Accuracy	90.9%
Sensitivity	94%
Error	8%
False Alarm Rate	2.56%
Specificity	95.4%
Precision	91.03%
F-1 Score	.95

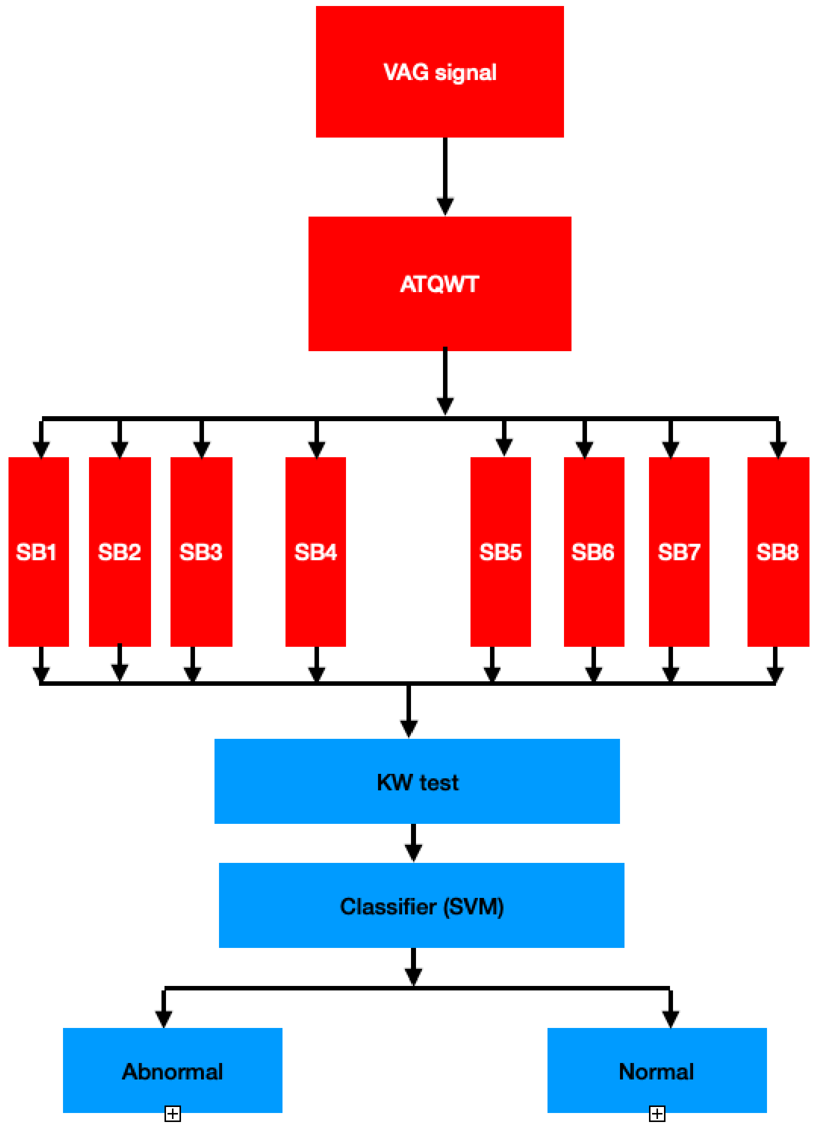

Figure 3.1: Work Flow

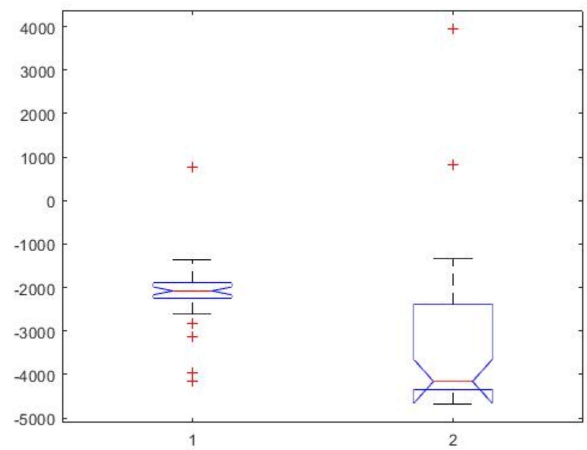

Figure 3.2: KW TEST (LOG ENERGY ENTROPY).

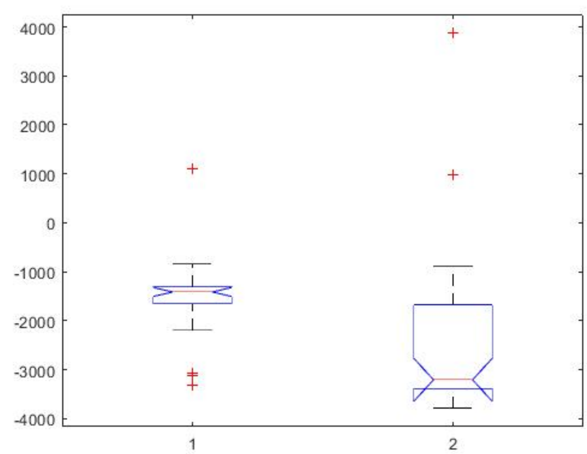

Figure 3.3: KW TEST (SURE ENTROPY).

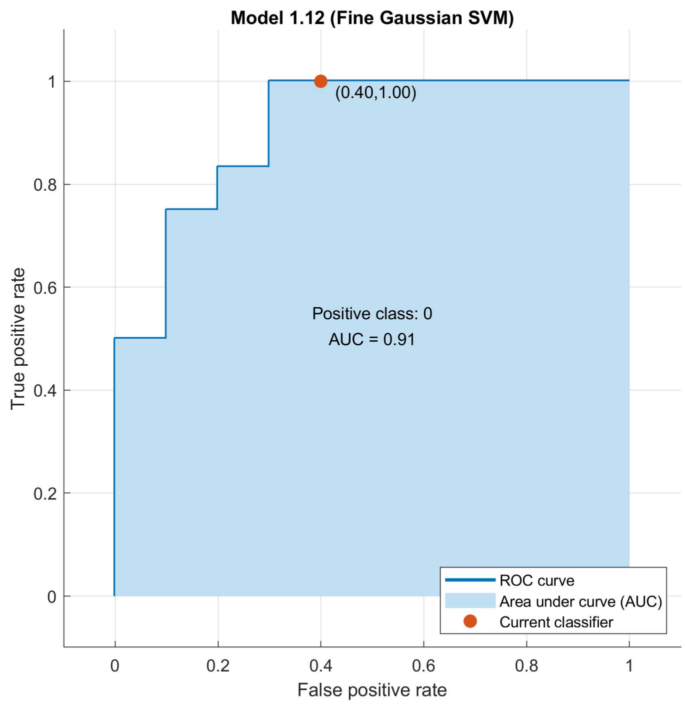

Figure 3.4: Area under curve (AUC)

.

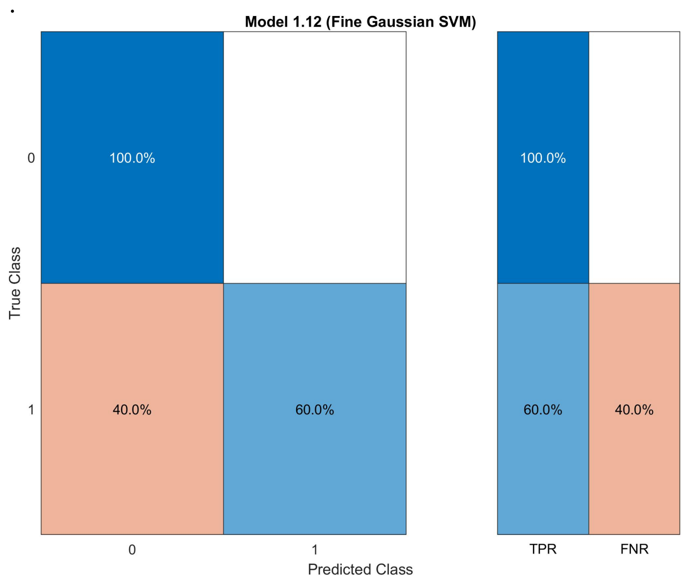

Figure 3.5: Confusion matrix

.

Chapter 4

Conclusion

We have studied two decomposition methods based on empirical mode decomposition (EMD) and adaptive tunable Q-wavelet transform (ATQWT) for improved diagnosis of knee-joint abnormalities. The statistical parameters have been computed from the IMFs, and ATQWT SBs. It has been observed that all the extracted parameters are not suitable for detection. Extraction and selection of the most suitable features from the VAG signals is a tedious complicated task. In this thesis applications of EMD and ATQWT have been investigated to discriminate the normal and abnormal VAG signals more efficiently. EMD is one of the most useful techniques to decompose any complex and non-stationary signal in the form of narrow band oscillatory functions named Intrinsic mode of functions (IMFs). Features such as mean, root mean squared, standard deviation, log energy entropy, norm entropy, Shannon entropy, threshold entropy, sure entropy, permutation entropy, skewness, kurtosis, and simple square integral has been extracted from each IMFs of every signal. To find the most relevant features, a non-parametric K-W test is applied. The TQWT algorithm is widely used in the biomedical data processing. In terms of configurable Q factor, it differs from standard WT. The generation one LPS and numerous HPS are produced as a result of the input signal's decomposition by TQWT. The VAG signal must be decomposed by TQWT using the tuning parameters quality factor (Q), oversampling rate (r), and a number of decomposition levels (J). One LPS and one J HPS levels arise from the decomposition of the signal with J level. Selection of the most suitable decomposition parameters for TQWT is a complicated task, therefore we utilized the ATQWT method for better discrimination. The study's findings lead to the conclusion that the ATQWT provides the better results compared to the EMD. Entropy-based characteristics work best for differentiating between VAG signals that are normal and those that are influenced by knee joint problems. Support Vector Machine (SVM), provides the highest classification accuracy of 90.8%.

Bibliography

[1] Janos Abonyi and Ferenc Szeifert. Supervised fuzzy clustering for the identification of fuzzy classifiers. *Pattern Recognition Letters*, 24(14):2195–2207, 2003.

[2] AMEER Ali, MOHAMMED Alrubei, LAITH FALAH MOHAMMED Hassan, M Al-Ja'afari, and SAIF Abdulwahed. Diabetes classification based on knn. *IIUM Eng. J*, 21(1):175–181, 2020.

[3] Serap Aydın, Hamdi Melih Saraoğlu, and Sadık Kara. Log energy entropy-based eeg classification with multilayer neural networks in seizure. *Annals of biomedical engineering*, 37(12):2626, 2009.

[4] Albert Ayenu-Prah and Nii Attoh-Okine. A criterion for selecting relevant intrinsic mode functions in empirical mode decomposition. *Advances in Adaptive Data Analysis*, 2(01):1–24, 2010.

[5] Varun Bajaj and Ram Bilas Pachori. Classification of seizure and nonseizure eeg signals using empirical mode decomposition. *IEEE Transactions on Information Technology in Biomedicine*, 16(6):1135–1142, 2011.

[6] Varun Bajaj and Ram Bilas Pachori. Eeg signal classification using empirical mode decomposition and support vector machine. In *Proceedings of the International Conference on Soft Computing for Problem Solving (SocProS 2011) December 20-22, 2011*, pages 623–635. Springer, 2012.

[7] Nima Befrui, Jens Elsner, Achim Flesser, Jacqueline Huvanandana, Oussama Jarrousse, Tuan Nam Le, Marcus Müller, Walther HW Schulze, Stefan Taing, and Simon Weidert. Vibroarthrography for early detection of knee osteoarthritis using normalized frequency features. *Medical & biological engineering & computing*, 56(8):1499–1514, 2018.

[8] Daniel Berrar. Bayes' theorem and naive bayes classifier. *Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics; Elsevier Science Publisher: Amsterdam, The Netherlands*, pages 403–412, 2018.

[9] Suxian Cai, Shanshan Yang, Fang Zheng, Meng Lu, Yunfeng Wu, and Sridhar Krishnan. Knee joint vibration signal analysis with matching pursuit decomposition and dynamic weighted classifier fusion. *Computational and mathematical methods in medicine*, 2013, 2013.

[10] Vladimir Cherkassky and Yunqian Ma. Practical selection of svm parameters and noise estimation for svm regression. *Neural networks*, 17(1):113–126, 2004.

[11] Marion Chevalier, Nicolas Thome, Matthieu Cord, Jérôme Fournier, Gilles Henaff, and Elodie Dusch. Lr-cnn for fine-grained classification

with varying resolution. In *2015 IEEE International Conference on Image Processing (ICIP)*, pages 3101–3105. IEEE, 2015.

[12] Patrick Flandrin, Gabriel Rilling, and Paulo Goncalves. Empirical mode decomposition as a filter bank. *IEEE signal processing letters*, 11(2):112–114, 2004.

[13] Richard A Groeneveld and Glen Meeden. Measuring skewness and kurtosis. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 33(4):391–399, 1984.

[14] Kapil Gupta, Varun Bajaj, and Irshad Ahmad Ansari. Osacn-net: Automated classification of sleep apnea using deep learning model and smoothed gabor spectrograms of ecg signal. *IEEE Transactions on Instrumentation and Measurement*, 2021.

[15] Agastinose Ronickom Jac Fredo, Thomas Raj Josena, Rajkumar Palaniappan, and Asaithambi Mythili. Classification of normal and knee joint disorder vibroarthrographic signals using multifractals and support vector machines. *Biomedical Engineering: Applications, Basis and Communications*, 29(03):1750016, 2017.

[16] Smith K Khare, Varun Bajaj, and Ganesh Ram Sinha. Adaptive tunable q wavelet transform-based emotion identification. *IEEE transactions on instrumentation and measurement*, 69(12):9609–9617, 2020.

[17] Sridhar Krishnan. *Adaptive signal processing techniques for analysis of knee joint vibroarthrographic signals*. University of Calgary, 1999.

[18] Sridhar Krishnan, Rangaraj M Rangayyan, G Douglas Bell, and Cyril B Frank. Adaptive time-frequency analysis of knee joint vibroarthrographic signals for noninvasive screening of articular cartilage pathology. *IEEE Transactions on Biomedical Engineering*, 47(6):773–783, 2000.

[19] Margarida Machado, Paulo Flores, JC Pimenta Claro, Jorge Ambrósio, Miguel Silva, António Completo, and Hamid M Lankarani. Development of a planar multibody model of the human knee joint. *Nonlinear Dynamics*, 60(3):459–478, 2010.

[20] RR Majhi, S Chattopadhyay, and A Ghosh. Analysis of electrocardiogram by radar and dwt based kurtosis comparison. In *Michael Faraday IET International Summit 2015*, pages 621–625. IET, 2015.

[21] Edwin Mascarenhas, Saif Nalband, AR Jack Fredo, and A Amalin Prince. Analysis and classification of vibroarthrographic signals using tuneable 'q'wavelet transform. In *2020 7th International Conference on Signal Processing and Integrated Networks (SPIN)*, pages 65–70. IEEE, 2020.

[22] Patrick E McKight and Julius Najab. Kruskal-wallis test. *The corsini encyclopedia of psychology*, pages 1–1, 2010.

[23] Sky McKinley and Megan Levine. Cubic spline interpolation. *College of the Redwoods*, 45(1):1049–1060, 1998.

[24] Saif Nalband, RR Sreekrishna, and A Amalin Prince. Analysis of knee joint vibration signals using ensemble empirical mode decomposition. *Procedia Computer Science*, 89:820–827, 2016.

[25] Saif Nalband, CA Valliappan, A Amalin Prince, and Anita Agrawal. Time-frequency based feature extraction for the analysis of vibroarthographic signals. *Computers & Electrical Engineering*, 69:720–731, 2018.

[26] Seung-Hyeon Oh, Yu-Ri Lee, and Hyoung-Nam Kim. A novel eeg feature extraction method using hjorth parameter. *International Journal of Electronics and Electrical Engineering*, 2(2):106–110, 2014.

[27] Ram Bilas Pachori and Varun Bajaj. Analysis of normal and epileptic seizure eeg signals using empirical mode decomposition. *Computer methods and programs in biomedicine*, 104(3):373–381, 2011.

[28] J. Ross Quinlan. Learning decision tree classifiers. *ACM Computing Surveys (CSUR)*, 28(1):71–72, 1996.

[29] Venkatesh Rajagopal et al. Machine learning based identification and classification of disorders in human knee joint-computational approach. 2021.

[30] Rangaraj M Rangayyan, Sridhar Krishnan, G Douglas Bell, Cyril B Frank, and Katherine O Ladly. Parametric representation and screening of knee joint vibroarthrographic signals. *IEEE Transactions on Biomedical Engineering*, 44(11):1068–1074, 1997.

[31] Rangaraj M Rangayyan, Faraz Oloumi, Yunfeng Wu, and Suxian Cai. Fractal analysis of knee-joint vibroarthrographic signals via power spectral analysis. *Biomedical Signal Processing and Control*, 8(1):23–29, 2013.

[32] Rangaraj M Rangayyan and YF Wu. Screening of knee-joint vibroarthrographic signals using statistical parameters and radial basis functions. *Medical & biological engineering & computing*, 46(3):223–232, 2008.

[33] Rangaraj M Rangayyan and Yunfeng Wu. Analysis of vibroarthrographic signals with features related to signal variability and radial-basis functions. *Annals of biomedical engineering*, 37(1):156–163, 2009.

[34] Rangaraj M Rangayyan and Yunfeng Wu. Screening of knee-joint vibroarthrographic signals using probability density functions estimated with parzen windows. *Biomedical Signal Processing and Control*, 5(1):53–58, 2010.

[35] Irina Rish et al. An empirical study of the naive bayes classifier. In *IJCAI 2001 workshop on empirical methods in artificial intelligence*, volume 3, pages 41–46, 2001.

[36] Manish Sharma and U Rajendra Acharya. Analysis of knee-joint vibroarthographic signals using bandwidth-duration localized three-channel filter bank. *Computers & Electrical Engineering*, 72:191–202, 2018.

[37] Manish Sharma, Pragya Sharma, Ram Bilas Pachori, and Vikram M Gadre. Double density dual-tree complex wavelet transform-based features for automated screening of knee-joint vibroarthrographic signals. In *Machine Intelligence and Signal Analysis*, pages 279–290. Springer, 2019.

[38] Robert C Sharpley and Vesselin Vatchev. Analysis of the intrinsic mode functions. *Constructive Approximation*, 24(1):17–47, 2006.

[39] Mrunal M Shidore, Shreeram S Athreya, Shantanu Deshpande, and Rajesh Jalnekar. Screening of knee-joint vibroarthrographic signals using time and spectral domain features. *Biomedical Signal Processing and Control*, 68:102808, 2021.

[40] Siuly Siuly, Smith K Khare, Varun Bajaj, Hua Wang, and Yanchun Zhang. A computerized method for automatic detection of schizophrenia using eeg signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(11):2390–2400, 2020.

[41] Karthikeyan Umapathy and Sridhar Krishnan. Modified local discriminant bases and its applications in signal classification [biomedical signal examples]. In *2004 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 2, pages ii–745. IEEE, 2004.

[42] Karthikeyan Umapathy and Sridhar Krishnan. Modified local discriminant bases algorithm and its application in analysis of human knee joint vibration signals. *IEEE Transactions on Biomedical Engineering*, 53(3):517–523, 2006.

[43] Yunfeng Wu, Sridhar Krishnan, and Rangaraj M Rangayyan. Computer-aided diagnosis of knee-joint disorders via vibroarthrographic signal analysis: a review. *Critical Reviews™ in Biomedical Engineering*, 38(2), 2010.

[44] Zongben Xu, Mingwei Dai, and Deyu Meng. Fast and efficient strategies for model selection of gaussian support vector machine. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 39(5):1292–1307, 2009.

[45] Meng Yang, Lei Zhang, Xiangchu Feng, and David Zhang. Sparse representation based fisher discrimination dictionary learning for image classification. *International Journal of Computer Vision*, 109(3):209–232, 2014.

[46] Shanshan Yang, Suxian Cai, Fang Zheng, Yunfeng Wu, Kaizhi Liu, Meihong Wu, Quan Zou, and Jian Chen. Representation of fluctuation features in pathological knee joint vibroarthrographic signals using kernel density modeling method. *Medical engineering & physics*, 36(10):1305–1311, 2014.

[47] Halil Yigit. A weighting approach for knn classifier. In *2013 international conference on electronics, computer and computation (ICECCO)*, pages 228–231. IEEE, 2013.