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Investigating an Efficient Filter to Implement Automated Nadi Pariksha by Analysing Time and Frequency Domain Features with Machine Learning Approach

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Abstract: In the realm of traditional Ayurveda practices, Nadi Pariksha (Pulse Diagnosis) stands out as a highly convenient and non-invasive method for examining the health of the human body. Rooted in ancient literature, Nadi Pariksha utilizes the radial artery pulse to assess the physiological condition. Recognizing the variability of pulses among individuals, influenced by factors such as age and time of day, mastering Nadi Pariksha has traditionally required personalized instruction from experts. Unfortunately, this specialized knowledge is at risk of fading away. To address this challenge, a sensor-based apparatus leveraging photoplethysmography is introduced which is designed to capture human pulse signals, facilitating the standardization and analysis of human Nadi. This innovative equipment comprises three pulse sensors, each dedicated to Vata, Pitta, and Kapha, alongside a microcontroller with an Analog-to-Digital converter connected to a laptop/PC via a COM port. In this study, pulse data from 250 volunteers, spanning ages 18 to 75 and representing a diverse mix of healthy and non-healthy individuals of both genders, underwent comprehensive analysis. A total of six pre-processing techniques, two types of features extraction methods to extract 60 features, and 3 classifiers were employed to distinguish healthy and non-healthy subjects. The comparison revealed that moving average and Butterworth filters exhibit higher accuracy in analyzing Nadi signals. The DT and KNN classifiers outshone others, achieving an impressive accuracy rate of 92%. This pioneering work holds significance for the analysis of Nadi signals and may pave the way for a new era of digitalization in Nadi Pariksha.

Keywords: Ayurveda, Feature Extraction, Pulse Diagnosis, Nadi Pariksha, Nadi Signal Analysis

1. Introduction

Ayurveda based *Nadi Pariksha* has history of thousand years. *Nadi pariksha* is one of the examination methods of ayurveda. *Nadi* pariksha can throw light on many imbalances of human body. It mainly comprises of three techniques, *Sparshna (Nadi Pariksha), Darshana* (seeing the patient) and *Prashna* (Interrogation of patient). *Nadi Pariksha* falls under category of sparshana. *Nadi Pariksha* is examination of wrist (Artery) pulse at a specific position. When holds the *nadi* for diagnosis, he/she may observe many parameters from the feeling on the fingertips. *Dosha* dominance reveals many facts about human body. Finding dosha dominance is certainly helpful to find out the disease. Traditional Nadi Pariksha (pulse diagnosis) if combined with modern theories from physics, informatics, hemodynamic, and other Disciplines will certainly help us to diagnose the patient status correctly [1]. Thus, pulse information has important clinical and physiological as well as psychological (mind) information in it. [2]. This study works on Nadi parameters to get some vital information so that the human health can be monitored. It is a non-invasive and complete examination method used to evaluate the physical and mental, emotional health of a particular person. By evaluating the wrist pulse at a special specific location on the left-hand wrist or right-hand wrist, an expert ayurveda practitioner can throw light on the imbalances in any human body. These imbalances are in the form of Vata, Pitta and Kapha, which are also called as Tridosha. These are foundational functional energies in the human body. VPK are formed from the five basic elements in the nature, called air, earth, space, water and fire [3]. These reveals are very important but at the same time very critical to be analyzed and requires a long practice. Now a days this art of expertise iis on the verge on vanishing. Every rhythm is connected to one or other health parameter [4]. It finds not only the physical ailments but also emotional, mental, psychological wellbeing of the human being. If the VPK doshas are correctly diagnosed, then the pulse parameters may reveal many diseases related information and can suggest few changes to one's lifestyle. Thus, Nadi pariksha can be considered as the holistic approach for advanced ayurvedic diagnosis system [5]. This wisdom can be further carried as an Indian cultural legacy. It will gain the market; it will be recognized as the bridging gap between the ancient ayurveda knowledge and modern day's healthcare practices. Computerized Nadi pariksha is a solution for the expert-based evaluation. The automated nadi pariksha will help diagnosing at the primary level and can suggest few remedies depending on the disease. A predictive diagnosis is possible in this case [6, 7].

This study aims to find out an efficient filtering technique for Nadi signals (Pulse signals). This study also focuses to investigate the feature extraction technique and an efficiently performing standard Machine learning algorithm. While investigating the efficient filter, the number of subjects, or adequate sample size is also investigated. This study facilitates the use of automated Nadi pariksha for routine use by society.

The research paper is organised as follows: Section 2 displays the related work study in the domain, section 3 addresses study contributions, section 4 elucidates the proposed methodology, and section 5 discusses the investigational results obtained. Section 6 concludes the paper by highlighting the findings and pointing out areas where future research could be beneficial.

2. Related Work

As this study aims to find a filter exhibiting superior denoising and classification performance choice for Nadi Pariksha, this section skeletons the work done in pulse diagnosis area focusing on the filters and their working. Researchers have dedicated substantial efforts towards advancing pulse diagnosis, demonstrating steady progress in the field [8–12]. This domain, while progressing slowly, has witnessed continuous development. The rapid growth of wearable devices has further enhanced the landscape, particularly in facilitating smart pulse diagnosis from the comfort of one's home [13]. Presently available pulse-taking instruments are typically worn around the human wrist and may involve pressure-exerting elements [10, 14, 15].

Properly applied pressure is crucial and requires expertise. Excessive pressure can impede blood flow to the fingertips, causing discomfort, while insufficient pressure may yield inaccurate pulse readings, as the sensors may not receive the correct signal [16]. Researchers commonly apply notch filters to eliminate unwanted frequencies, Preprocessing is a critical component, and a robust framework based on Frequency Dependent Analysis (FDA) has been presented, including a cascade filter to remove high-frequency noises and curve fitting for minimal signal distortion [16].

A standard pulse waveform shows three peaks: systolic, diastolic, and a reflected peak. Detecting minute changes in the waveform proves invaluable for classifying health conditions such as arterial stiffness and heart rate variability [12, 17–19].

Sensors play a pivotal role in pulse diagnosis, and researchers have explored diverse types, according to how flexible they are, what capacitance is, and what type of pressure they deal with. The choice of sensor depends on factors like sensitivity towards the change, time required to respond, pressure resolution, and a high Signal-to-Noise Ratio (SNR) to ensure applicable pulse detection. However, challenges persist in sensor fabrication [19]

Pulse data, being a weak physiological signal, is susceptible to interference from signals from other organs or power frequency interference [20].

Various preprocessing methods have been employed, considering that a Nadi Signal comprises a series of pulse segments that might be distorted during signal acquisition. Thus, normalization and segmentation are imperative [18, 21, 22].

Feature extraction plays a pivotal role in diagnosing health status. Selecting the correct features and analyzing the signal in depth is the requirement of higher accuracy. The signal representation stage is equally important. These steps significantly boost the working of machine learning models by increasing accuracy in foreseeing and identifying diseases.

Researchers have extracted features from frequency domain [23, 24], time domain [25, 26] time and frequency domain [27], features for analysis. Each domain gives several features, the most relevant can be extracted.

In this study, features are extracted using two methods, statistical wavelet domain features using one dimensional Discrete Wavelet Transform (1D-DWT) and Frequency information using Fast Fourier Transform (FFT). According to reviews, supervised machine learning techniques prove effective for health condition analysis and prediction tasks [28]. Godbole et al. have worked to predict image based pediatric pneumonia with CNN and transfer learning-based ensemble technique, with increase in time requirement the accuracy is found to be improved [29]. Goad et al. used machine learning ensemble technic to predict cardiovascular disease based on a dataset available for 70k individuals [30].

Deep learning is also used by many of them. Deep learning uses very huge dataset and long training time; hence this study focuses on machine learning techniques [31, 32]. Acquiring real-world datasets poses challenges, prompting researchers to explore novel methods for generating pulse data [33].

While the previous studies have explored many aspects of the pulse diagnosis area, in India, automated/computerized Nadi Pariksha is a less explored field. These studies primarily focused on known statistical methods and smaller datasets, while haven't paid much attention to the varied range of preprocessing techniques, feature extraction methods, advanced machine learning algorithms which directly contribute to predictive accuracy. Although few researchers have worked on it, the Nadi signal dataset is not readily available on the internet. This study aims to satisfy the gap by leveraging larger datasets, advance filtering techniques, employing the combined feature extraction method, implementing machine learning models to achieve the desired results.

3. Research Contributions

This study is focused on traditional approach towards finding the common yet potent insights into human health. After reviewing related literature, the research papers devoted to traditional Indian Nadi Pariksha work are found to be very few. The machine learning approach for sensor-based Nadi Pariksha is still to be explored much. The key contributions of this study include:

- Evaluating the capabilities of automated *Nadi Pariksha* (Pulse examination). This investigation aims to compare the performance against traditional diagnostic methods, highlighting their capability for inclusion into modern, technology-driven healthcare solutions.
- Assessing and employing several signal preprocessing approaches to detect and use most efficient filtering techniques to boost signal quality and remove noise. Most of the research papers employed single filter for the study work. This study employees 6 filtering techniques [34–37].
- Developing a comparative analysis of outcomes to design a strong structure for classifying healthy and non-healthy subjects based on key physiological and statistical parameters. The structure goals to apply advanced computational methods to improve accuracy and trustworthiness in classification for clinical and diagnostic applications. This study employees extracting statistical features along with time, frequency domain features and evaluates it based on machine learning approach which results in improved accuracy as compared to the studies employing statistical analysis of the features or extracting only on type of features [1, 31, 38–42].
- Examining a good number of subjects to enhance the statistical sturdiness and trustworthiness of the attained outcomes. This approach ensures greater generalizability and maintains extra precise implications for wider applications in the traditional Nadi Pariksha domain.

4. Proposed Methodology

The automated Nadi Pariksha starts with sensors and ends with the distinguished results. This work generally comprising of four major phases,

1) Signal acquisition.
2) Signal pre-processing.
3) Feature extraction
4) Classification

Figure 1 summarizes above phases for automated *Nadi Pariksha*, along with the methods used to achieve the purpose. In this study, the proposed methodology focuses on the pre-processing part of the general work. Various filters are applied to the acquired sensor data. Further that output is used to extract features with frequency and wavelet domain methods. These features undergo popular machine learning algorithms like SVM, DT, and KNN to distinguish between healthy and non-healthy subjects.

4.1 Signal Acquisition

Signal acquisition implies sampling signals that correspond to physical and real conditions, then by transforming them into digital numeric values for computer processing. Figure 2 shows the signal acquisition approach used in proposed methodology. Many researchers have used different types of sensors for the pulse diagnosis work. The piezoresistive sensor [39] The pressure sensor [40], optical sensor [43], pulse sensor [11, 44], even array of sensors [14] are used in the pulse diagnosis domain. While in India the pulse diagnosis field is still very less explored. Majority of researchers worked with pulse sensors. This study has employed three optical pulse sensors utilizing photoplethysmography. Principle to collect Nadi signals. The variation between the incoming light and outgoing light is considered for the signal acquisition [11]. These sensors detect slight shifts in human skin as blood vessels expand, providing more accurate results. The sensors require a voltage of +3v to +5v. Microcontroller: An Arduino Nano microcontroller connects the pulse sensor device to a laptop through the COM4 serial port at a baud rate of 9600. The microcontroller's built-in 12-bit A to D converter converts analog signals from the pulse sensor to digital data, which is then stored in a CSV file.

Figure 3 shows an actual working setup of study instrument.

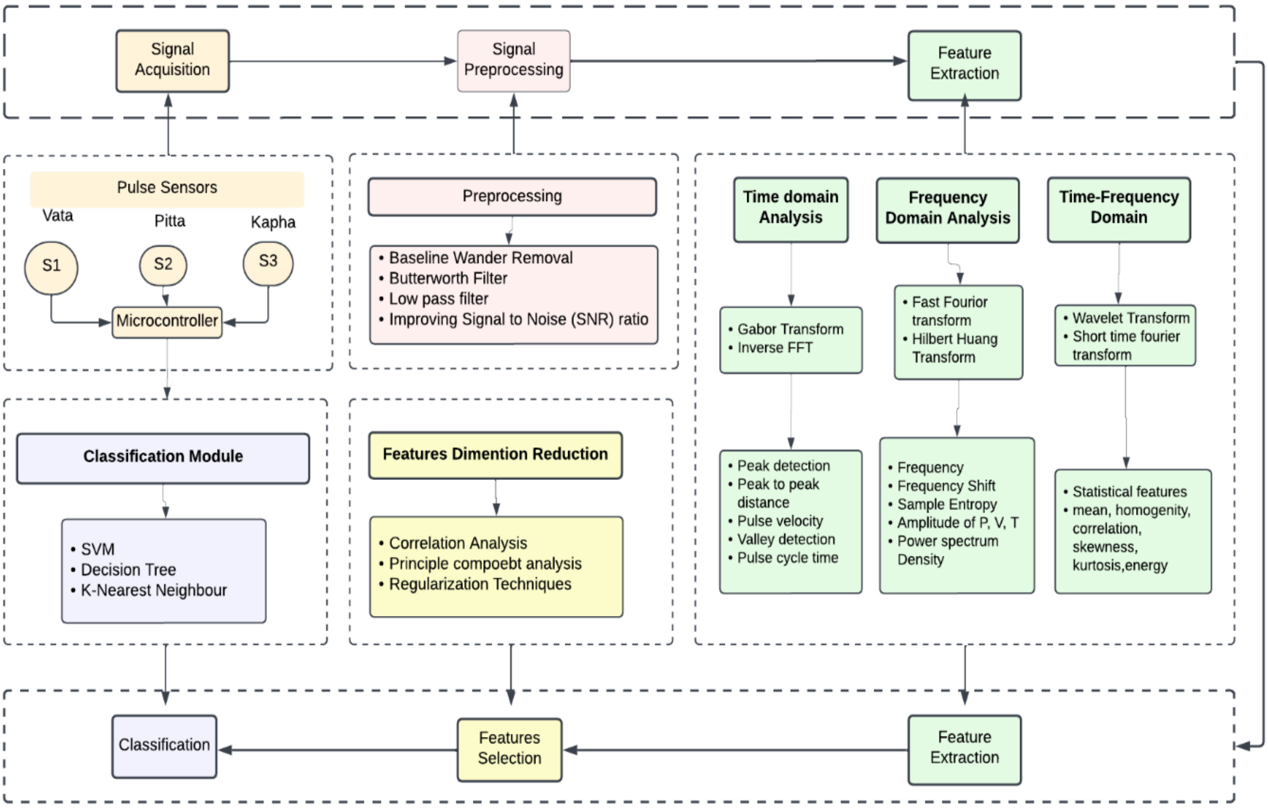

Figure 1. Proposed Methodology (Phases, methods and attributes) for Automated Nadi Pariksha

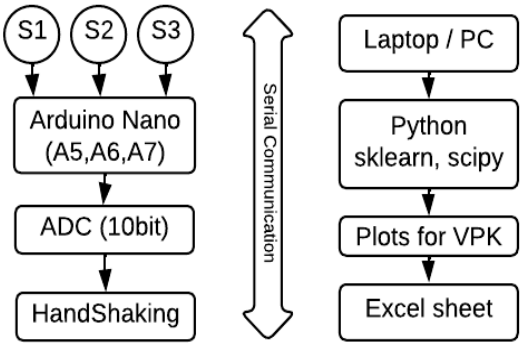

Figure 2. Signal Acquisition Approach of Proposed Methodology

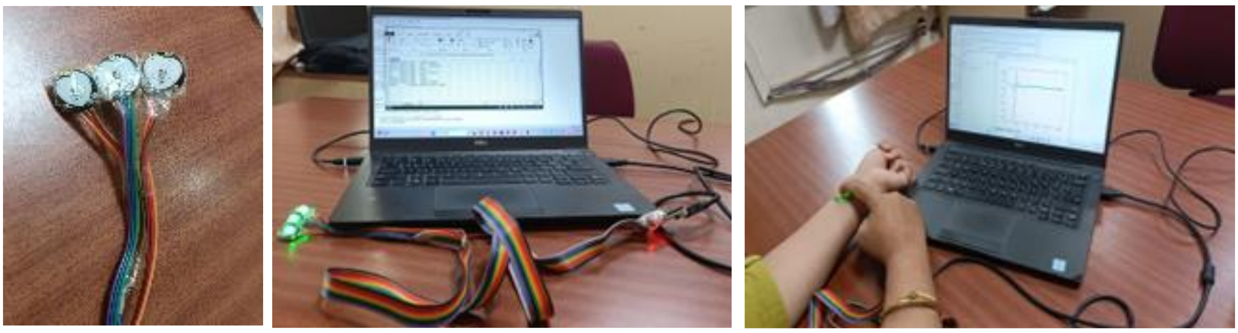

Figure 3. Signal Acquisition Setup

Figure 4. Taking Reading from Subject

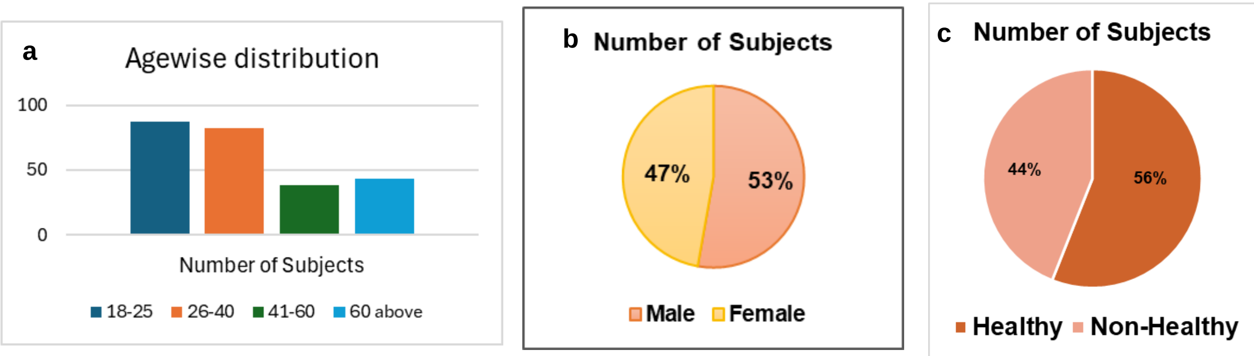

Figure 5 a. Age wise Data Distribution, b. Gender wise Data Distribution, c. Health status wise Data Distribution

Through signal acquisition, subjects provide information such as timestamp, name, age, gender, and existing health issues, followed by the acquisition of VPK readings. Using several library files available in python the operations like pre-processing feature extraction and classification are carried out.

Figure 4 shows an actual photograph of data collection from one of the subjects.

Dataset Generation: For dataset generation, participants are briefed on the study's purpose, and written consent is obtained. Subjects are asked to sit calmly, keeping their mobiles aside. Relaxation is emphasized to minimize activity-induced changes in pulse data signals

Pulses are exclusively collected from the female subjects' left hand, and from right hand for male subjects. According to the ancient literature the left side of the women and right side of men are more balanced as per ayurveda. Eventually the ayurveda practitioners adapted this method. But once you adapt and master the art of pulse diagnosis collecting the pulses from any side of the human body is also possible [2, 45, 46].

The study dataset comprises data from 250 individuals, male and female, healthy and non-healthy subjects aged 18 to 75, and the subject data summary is depicted in the chart shown in figure 5.a, 5.b. and 5.c. While the study was in progress, deciding number of samples (subjects) was a challenge. Many researchers have used different number of subjects for the study purpose, 90 subjects to distinguish patients with stable coronary heart disease [1], 200 subjects to assess and compare with traditional knowledge [26], prakriti analysis with 30 volunteers, [44], 83 subjects to classify between healthy and cholecystitis and nephritis affected individuals [47], to distinguish lung cancer with 36 subjects [48], experimental health monitoring with 55 subjects [49]. With these observed numbers, 250 subjects were selected for the proposed study. For the study, when discussed with ayurvedic practitioners, it is observed that all the individuals from the age group 18-25 tend to be healthier, hence few healthy individuals from this age category were necessary. Hence included in the study. To balance the dataset male female numbers were also important, hence male and female were also chosen according to requirement.

Among 250 subjects, 132 are male and remaining are female. The balance of healthy and non-healthy subjects is the most important criteria and hence 140 healthy and 110 non-healthy subjects were added to the dataset.

As of now for this study, the dataset comprising 250 individuals is used for building the model. In the future, as the work is progressing, the number of subjects will be continuously added to the dataset. Which will lead to a robust and efficient model. Also, the data regarding the specific illness will also be analyzed to improve the model's real-world applicability.

Mathematical presentation: of the acquired signal can be presented by, considering recorded signal as linear time-invariant (LTI), [50, 51] Impulse response-$h(n)$, acquired signal $y_{acq}(n)$ as production of filter when original input $x_{original}(n)$ is given,

$$y_{acq}(n) = x_{original}(n) * h(n). \tag{1}$$

As signal is not static, it is splitted into overlapping frames within which the signal is assumed to be stationary. So, the pth short-term frame of acquired input is,

$$Y_p w(f) = X_p w(f) H(f) \tag{2}$$

$H(f)$ is joined mathematical function that generated input signal, and the acquired signal $X_p w(f)$ can be perceived as original signal. $Y_p w(f)$ is the acquired signal.

So, the equivalent transfer function of the received signal at the sensor and recorded is considered as the source of the recorded signal. Therefore,

$$X_p w(f) = Xe_p w(f) X_v(f), H'(f) = H(f) X_v(f) \tag{3}$$

Where $Xe_p w(f)$ is the excitation function. $X_v(f)$ is the recorded signal transfer function in pth frame and $H'(f)$ is the equivalent transfer function that characterizes the signal.

$$Y_p w(f) = Xe_p w(f) H'(f) \tag{4}$$

4.2 Signal Pre-Processing

Several researchers have employed a variety of preprocessing techniques. As the Nadi signal is a subtle human body signal, accurate sampling is essential [21]. Electrostatic noise from power lines can compromise the signal. Therefore, a 60Hz notch filter was designed to counteract this interference. Other factors, such as breathing, subject movement, cable movements, sneezing, and inconsistent pressure on sensors during data collection, can lead to baseline wandering. Numerous techniques have been proposed by scholars for preprocessing. The decision to compare these methods was motivated by the goal of identifying the most effective one for future research. Notable methods include Butterworth [11], Wavelet [14, 52–55], Median [17, 56], Spline [57]. The selection process considered for filter choice includes many criteria such as noise reduction, signal smoothing process, trend analysis, computational feasibility, real world applications, and how previous researchers have used them for similar data and versatility. Each filter which is chosen appears with some or other unique feature, strength. Like moving average filter shows computational efficiency, smoothening of data is also good. Minimal distortion with flat frequency response is the uniqueness of Butterworth filter. Savitzky-Golay filter offers polynomial fitting, whereas wavelet filter offers non-stationary signal handling in an effective manner [58]. Spline filter maintains the continuity of the signal whereas median filter removes impulsive noise and preserves edge details.

Other filters such as Gaussian, Kalman etc. are not considered for the study as they may be lacking in scope alignment, as well as comes with high computational complexity. This study tried balancing the diversity of filters with the outcome [59]. This study focuses on the study of filters, which are useful for the Nadi signal analysis. This study implemented the following filters and measured their performance in classifying the healthy and non-healthy subjects. Figure 6 shows the filters implemented for the experimentation. Filters are from finite impulse response (FIR), infinite impulse response (IIR), linear or non-linear in working, from time, frequency, or wavelet domain category. Figure 7 - 12 are graphs, which are generated during the signal preprocessing phase and show the difference between the original and preprocessed signal data from sensor signal. Matplotlib from python is used to plot these graphs.

4.2.1 Moving Average Filter (Basel)

It is a filter from time domain. This filter is suitable if the data available is in time-series format. It removes noise and short-term fluctuations and preserves its long-term trends. It takes average of a specified number of adjacent data points (sliding window) and gives this average as the filtered output [37].

$$y[n] = \frac{1}{n} \sum_{k=0}^{N-1} x[n-k] \tag{5}$$

Where, $x[n]$ = Optical sensor data.

N = window size

x[n-k]= kth most recent data point.

Moving average filter effectively smooths high frequency noise and variation. It is advantageous as it works with only past and present data point. Figure 7 shows the comparison between original sensor data and pre-processed data. Here the change can be observed.

4.2.2 Wavelet Based Denoising

It is a wavelet domain filter. The original signal is decomposed using wavelet transform into distinct frequency components represented by wavelet coefficients [35].

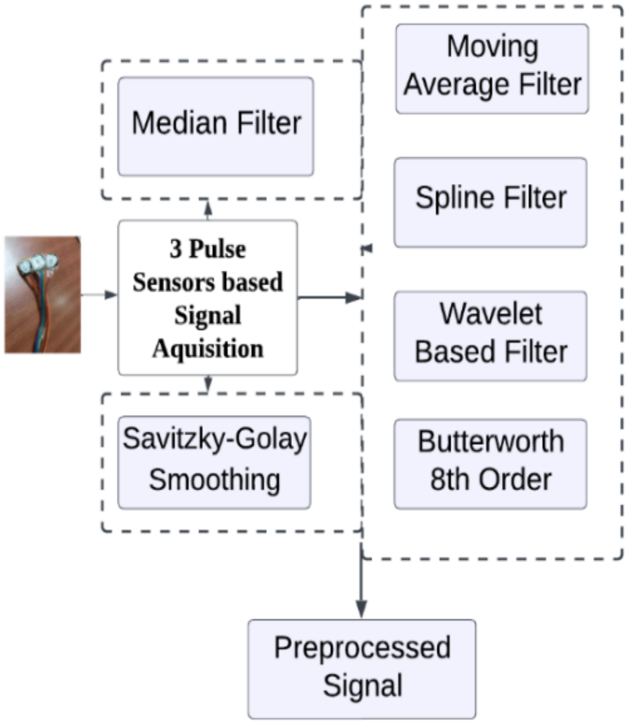

Figure 6. Implemented Pre-Processing Methods

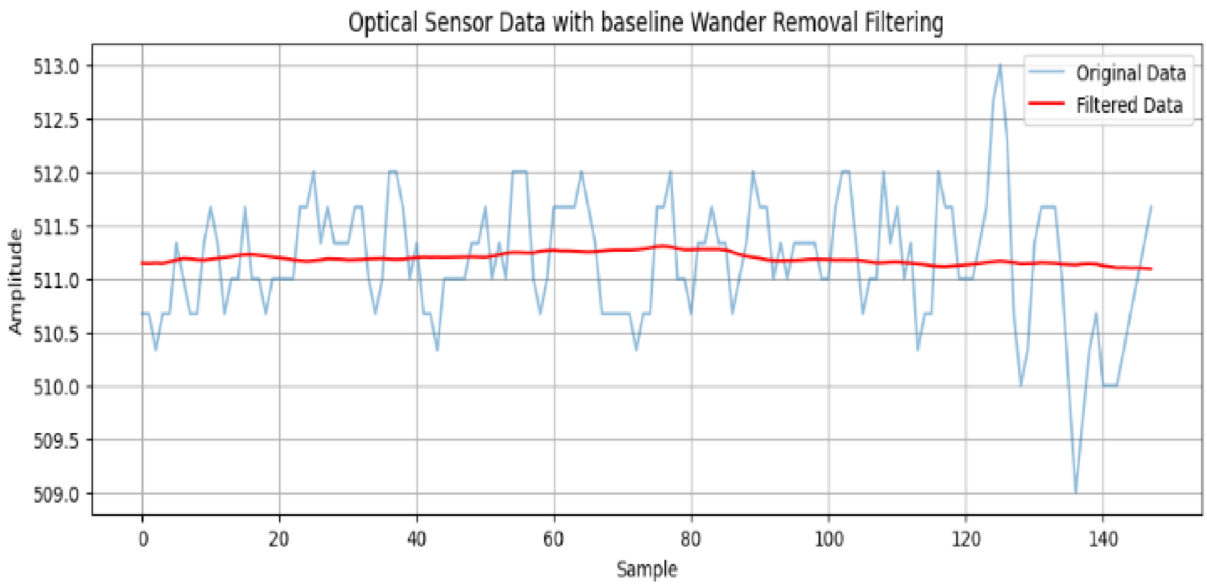

Figure 7. Moving Average Filter

$$W(a,b) = \int_{-c0}^{c6} x(t).\psi_{a,b}(t)\,dt. \quad (6)$$

Where $W(a,b)$ = Wavelet coefficient at scale a & position b, $x(t)$ is the input signal (optical sensor data), $\psi_{a,b(t)}$ = scaled & translated wavelet function. The thresholding is done and then the signal is reconstructed with inverse wavelet transform.

$$y_{denoised}(t) = \sum_{a,b} W(a,b) \cdot \phi_{a,b}\,(t) \quad (7)$$

Where $y_{denoised}(t)$ = denoised optical sensor data, $\phi_{a,b}\,(t)$ = scaled & translated scaling function.

Figure 8 shows the before and after change in sensor signal using Butterworth filter data.

4.2.3 Spline Filtering

It is again a time domain-based filter. It is a technique for smoothing or approximately data by fitting cubic splines to the data points. IT uses spline interpolation techniques. Smoothing factors can be changed according to the requirements. Here data representation is(x_1, y_1) , (x_2, y_2) ……….(x_n, y_n) , these all are data points, obtained from the optical sensors where x represents time or position, & y represents the observed values. Then cubic spline, a piecewise cubic polynomial is defined. Figure 9 shows the change in signal after applying spline filter.

$$s_p(x) = e_p(x-x_p)^3 + f_p(x-x_p)^2 + g_p(x-x_p) + h_p \quad (8)$$

a, b, c, d are coefficients for each segment The common derivative constraints are applied.

$$S_p'(x_i) = S_{p+1}'(x_i)\ S_p''(x_i) = S_{p+1}''(x_i) \quad (9)$$

Which in turn derives equations that relate coefficients e, f, g & h. After solving these, equations (linear) coefficients e, f, g, & h are determined [36].

4.2.4 Median Filter

A median filter is a time domain filter. It is a non-linear filtering technique that substitutes every data point in a signal with the median data point within an indicated window centred on that point. Window size plays an important role choice of window size is dependent on your requirement (your signal & noise) if your noise shows small spikes, then smaller window size is suitable, whereas if noise is continuous or spread out then larger window size is effective. A special type of handling is required towards the edge of the data points, where the window cannot be formed. These filters have excellent edge perseverance and noise elimination capacity [47]. The filtering operation can be preserved as

$$W[n] = [\,x_{original}[n-(M-1)/2], x_{original}[n-(M-1)/2+1], \ldots [\,x_{original}\ [n+(M-1)/2-1]\ +(M-1)/2]]$$

$y_p[n]$ = median ($W[n]$)

$$y_p[n] = x_{original}[n] * h[n] \quad (10)$$

Where, M = window size, $x[n]$ = data point of original signal, $W[n]$ = all window points, $y[n]$ = median calculated, $h[n]$ = impulse response of the median filter. Figure 15 shows the change in signal after applying median filter.

4.2.5 Butterworth Filter

It is a linear signal processing filter, known for its smooth and maximally flat frequency response in the pass band. These are based on IIR technique and work as analog low-pass filters. It allows all frequencies in the pass band to pass through with equal gain, making it ideal for, applications with that response. The performance is dependent on order N and normalization frequency. It has many orders and higher order filter have steeper roll-off rates. It has smooth and slowly decaying envelop. The mathematical function can be written as

$$H(s) = \frac{1}{1+\left(\frac{8}{\omega_c}\right)^{2N}} \quad (11)$$

where, $H(s)$ = Laplace domain transfer function

S = Complex frequency variable

ω_c = Cutoff frequency

N = filter order.

Butterworth filter can be evaluated using SNR, MSE, frequency response analysis, phase response analysis or impulse response analysis. Figure 11 shows the raw and filtered data [34, 37, 50].

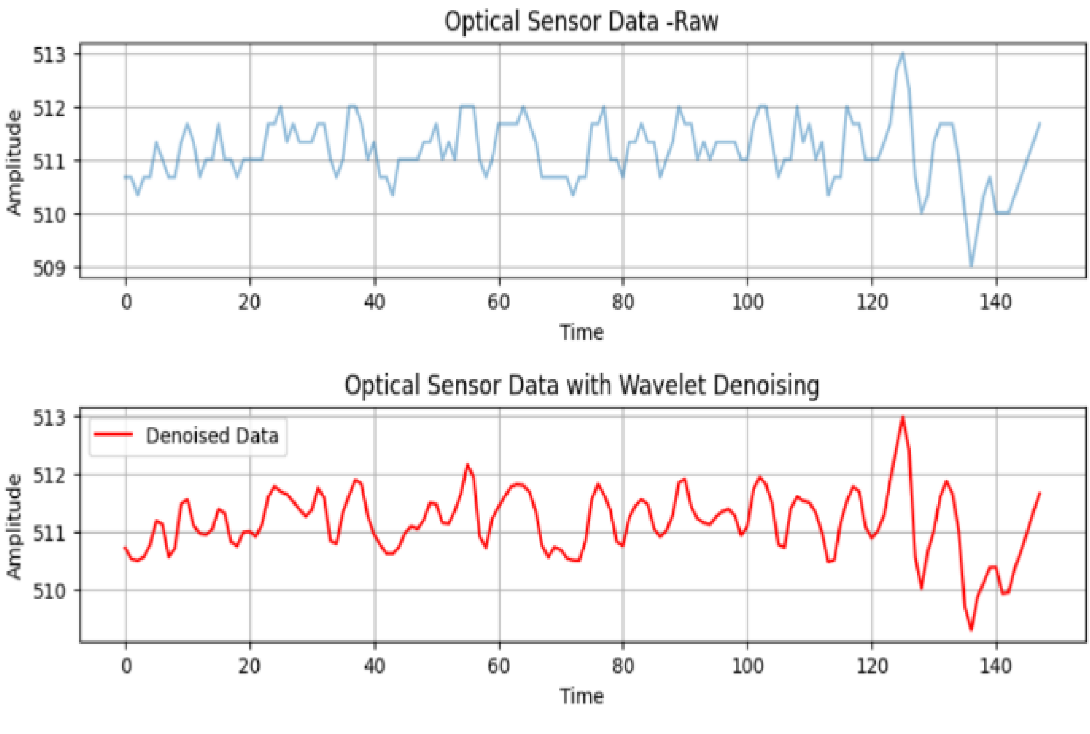

Figure 8. Wavelet Based Denoising

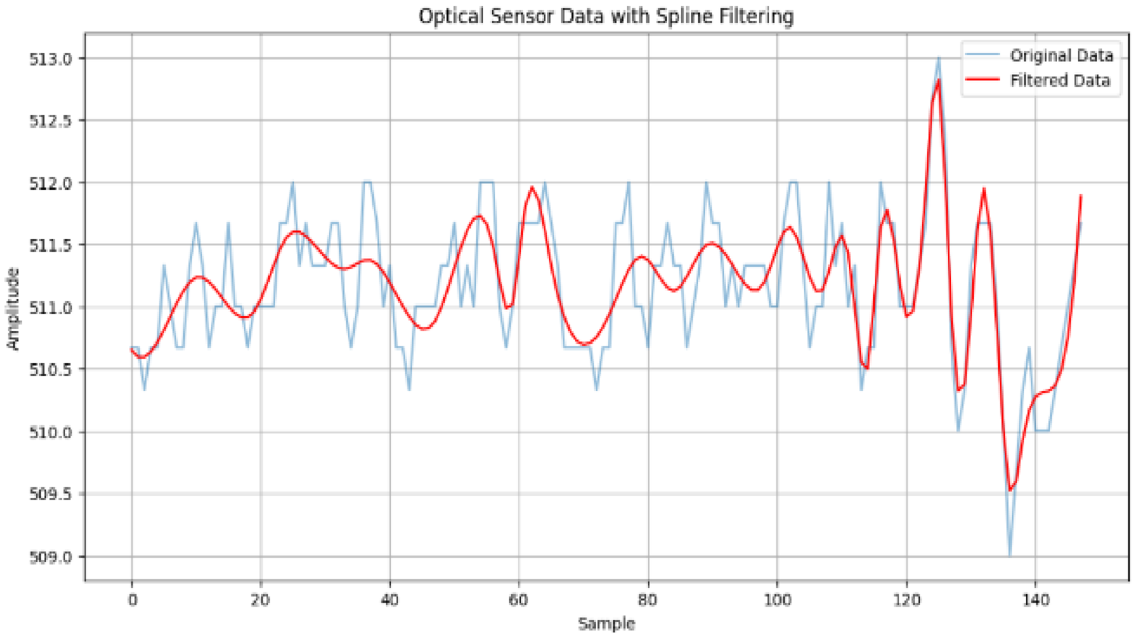

Figure 9. Spline Filter

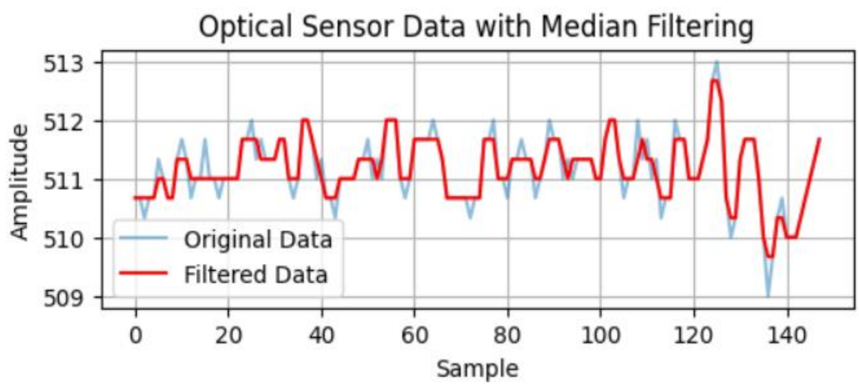

Figure 10. Median Filtering

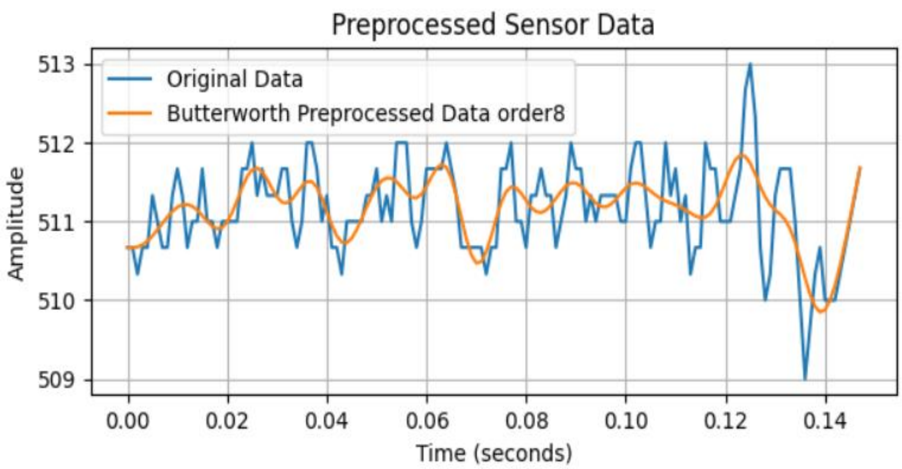

Figure 11. Butterworth Filter Order 8

This study implemented order 8 filter. It is observed that the lower order filter works like a Gaussian filter [37] and order 8 doesn't tend to produce any peaks [34].

4.2.6 Savitzky – Golay Smoothing (Savgol) Filter

It is a FIR filtering technique. Also referred as polynomial smoothing or least squares smoothing. It preserves the high frequency data in the original signal; hence it is useful in preserving specific features of the signal. It is useful in medical signal processing, as many times it is acceptable to keep high frequency peaks in original signal to be preserved [50]. It is a linear convolutional based method for polynomial curve filtering and smoothing. Figure 12 shows how the signal changed with savgol filter.

$$y[n] = \sum_{m=-M}^{M} b0\, x\,(n+m) \qquad (12)$$

where, $y[n]$ = Output in convolutional form with window length N

$b0$= Filter with impulse response

$x\ [n+m]$ = Optical sensors data points.

4.3 Feature Extraction

Feature extraction is a crucial step that converts the processed data into a collection of features, providing an accurate representation of pulse waveforms by capturing time-based (temporal), structural or morphological, and frequency related characteristics. Simultaneously, feature selection aims towards dimensionality reduction by identifying the most significant and revealing features, to progress with performance competence, and preventing over fitting. In essence, extraction and dimensionality reduction contribute towards effectively representing signals and identifying crucial features.

These steps significantly boost the working of machine learning models by increasing accuracy in foreseeing and identifying disorders. Feature extraction characterizes the signal's behaviour. These features are extracted and analysed to assess various aspects of subject's health. Different features may be more relevant for different applications [60]. This study as said earlier, extracts features using 1D-DWT and FFT methods. From wavelet domain, statistical and frequency features are extracted. In all 60 features were extracted, 20 unique features for Vata, Pitta and Kapha sensors each. While the list of features was decided for the study, it has been considered that these features must be relevant to the work. Their performance was validated to gain the optimal accuracy. The dimensionality of the dataset is taken into consideration, and most important features were chosen for the work. Figure 13 shows the list of time and frequency domain features extracted from sensor signal data using wavelet and frequency domain feature extraction methods.

4.3.1 Wavelet Domain Features

Feature extraction using 1D-DWT [38, 61] is implemented. Wavelet transform decomposes the signal data and returns the high frequency and low frequency components. They are also called as approximate and detail components.

DWT works on the principal of averaging the adjacent frequencies. The accompanying figure 14 visually illustrates the decomposition process. These number of decomposition layers are determined depending on the analysed data and the need of the project [38]. This study used decomposition till layer 2.

The signal is decomposed into 2 layers. The signal can be written as summation of the high frequency part and low frequency part of the signal as shown in equation. You may decompose it further if required. Here it is limited to 2 level decomposition.

$$Signal = cA_1 + cD_1 = cA_2 + cD_2 + cD_1 \qquad (13)$$

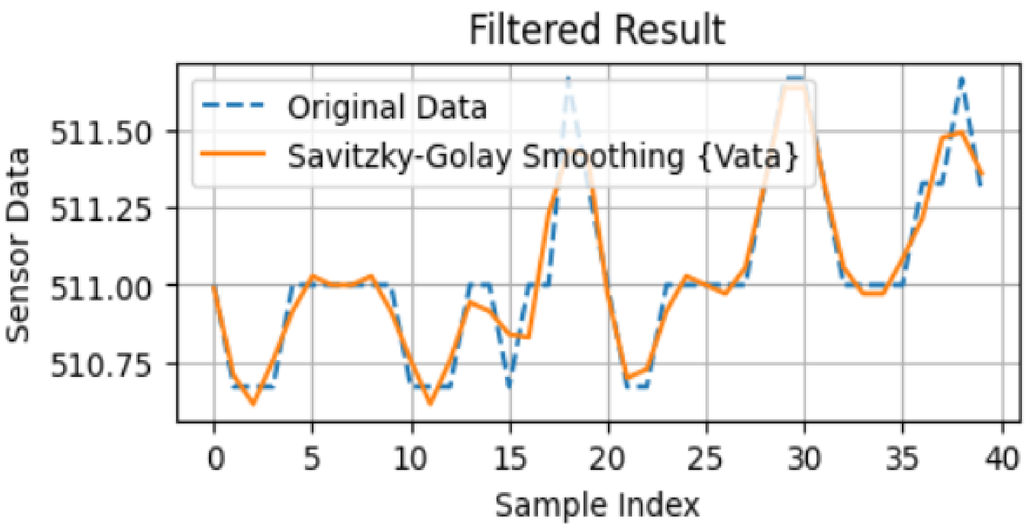

Figure 12. Savitzky – Golay Smoothing

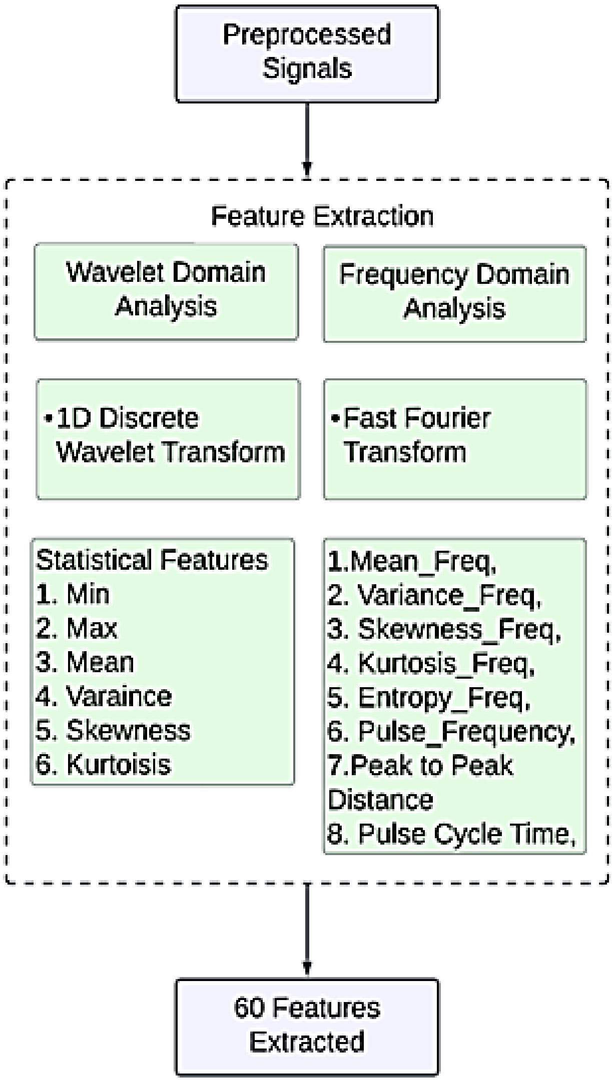

Figure 13. List of Features Extracted

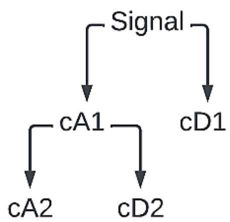

Figure 14. Wavelet Decomposition Levels

From approximate component 6 features and from detail component 6 features were extracted. Hence 12 features per sensor, comprises to 36 features for VPK signals in total. Figure 15 (a-d) shows the kernel density estimate (KDE) visualization, plotted using python, for few extracted features for healthy versus non-healthy subjects (overall, as per age group, male and female), which gives insight on how the feature values vary according to health status, age, gender. Understanding the features will lead us to an efficient classifier choice.

4.3.2 Frequency Domain Features

FFT is deployed to extract frequency information from the pre-processed data [41, 42]. Total 8 features per signal were extracted which sums up to 24 features for VPK signal.

Below figure 16 (a-c) shows the KDE plots for few important features, which gives insight on how the feature values vary according to health status, age, gender. Understanding the features will lead us to an efficient classifier choice.

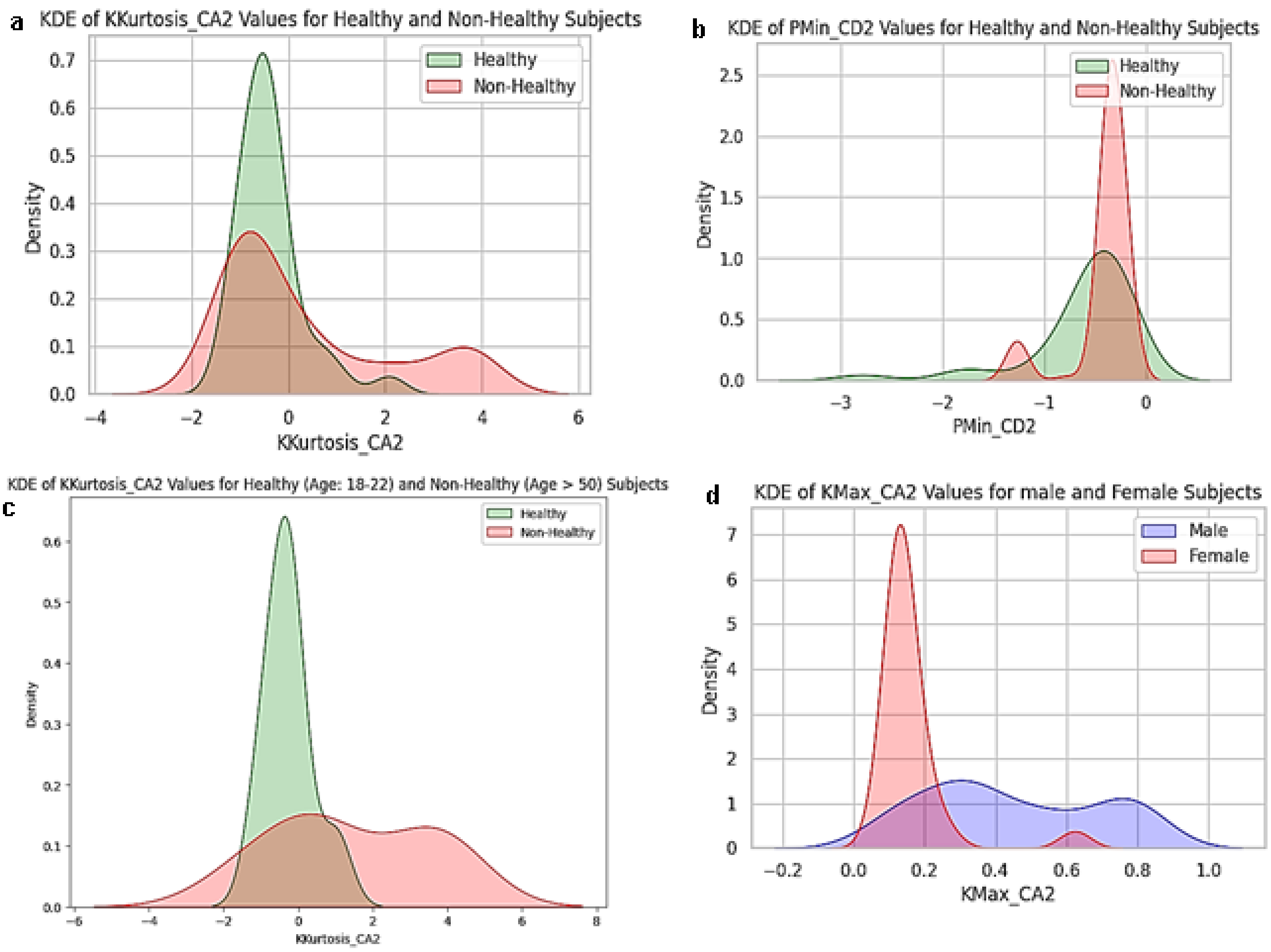

Figure 15 a. Kapha Kurtoisis_CA2, **b.** Pitta Min_CD2, **c.** Kapha Kurtoisis_CA2, Healthy (Age < 22) Vs Non-Healthy (Age > 50), **d.** Kapha Max_CA2 (Male vs Female)

Figure 17 shows a heat map plotted using python, during the study, on the Basel filter, which confirms that important features are related with each other and the health status.

4.4 Classification

Many researchers have used statistical analysis on the extracted features, which has its own limitations [62–64]. This study used the machine learning (ML), it is a subset of artificial intelligence (AI) offers a wide variety of algorithm for quantitative analysis of *Nadi* waveforms. This may facilitate the accurate health condition diagnosis. Upon extracting various kind of features from the *Nadi* signal dataset the ML algorithms can mine important insights from it. Every kind of pulse parameter is used in extracting the minute details which leads towards disease diagnosis. Till date many researchers have employed a few ML algorithms in the pulse diagnosis area, like KNN [40, 65], SVM [31, 39, 66, 67], random forest [68], NN [26]. Here in this study standard machine learning algorithms are employed on the dataset for the further analysis. This study exhibits the results of SVM, DT and KNN. Figure 18 shows these classifiers. While the study achieves the working results, the hyper parameter tuning always played an important role in optimizing the classifier performance. Each of the classifier used has some specific hyper parameter, which contributes to the working nature of that algorithm. For SVM algorithm, the parameters like kernel type (either linear, polynomial or radial basis function) along with regularization parameter C and gamma value for RBF kernel, plays an important role in performance. They ensure the behaviour of an algorithm between underfitting and overfitting. For DT algorithm, hyper parameters like maximum depth of the tree, Gini index, minimum samples were tuned to get the maximum performance. This avoids the overfitting or underfitting of the model. To maintain the optimal balance between the bias and variance, the k value, that is number of neighbours are balanced. This ensures the best performance of the KNN algorithm in real world.

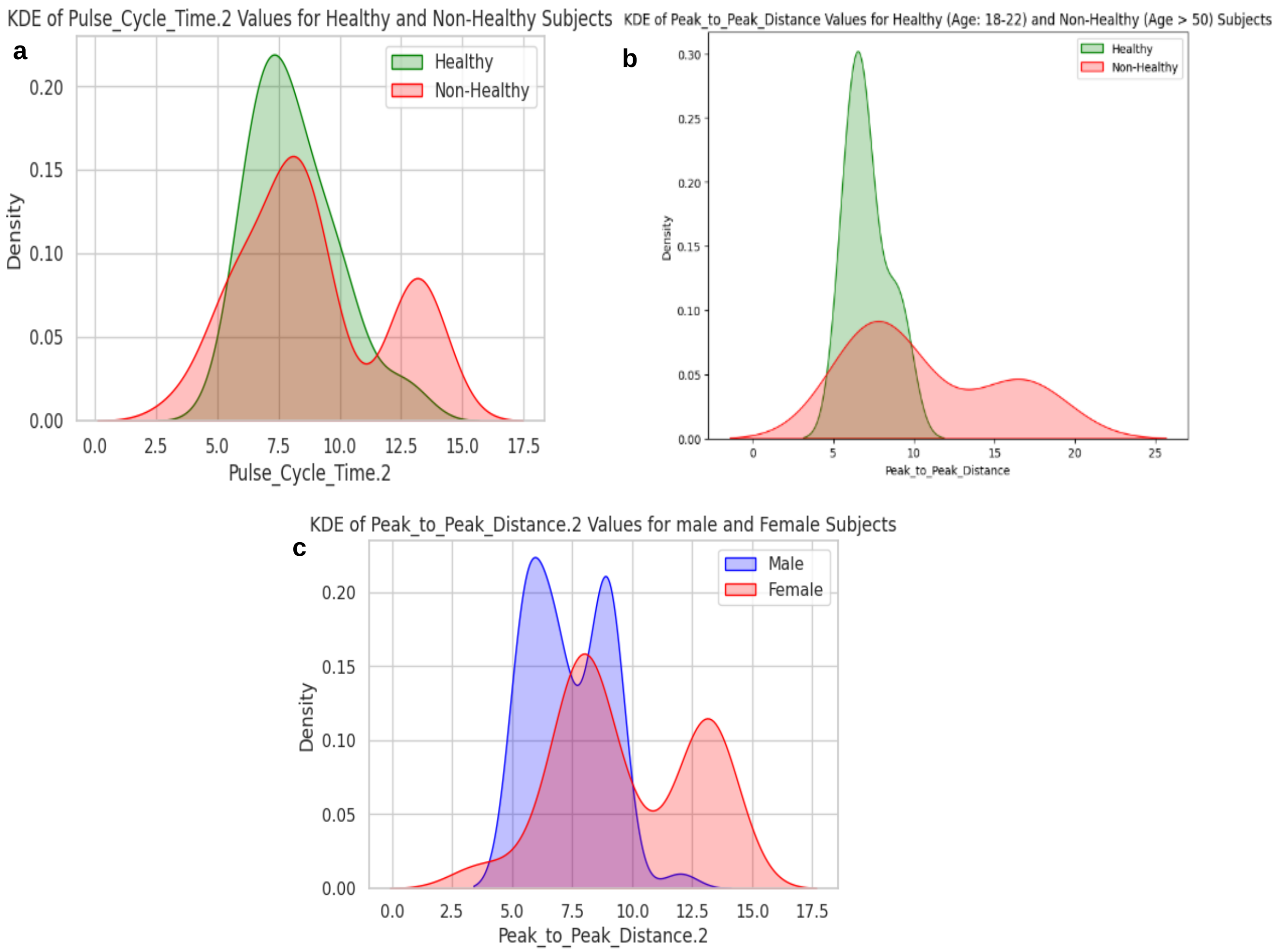

Figure 16a. Kapha Pulse_Cycle_Time, **b.** Vata Peak_to_Peak_Distance Healthy (Age < 22) Vs Non-Healthy (Age > 50), **c,** Kapha Peak_to_Peak_Distance (Male vs Female)

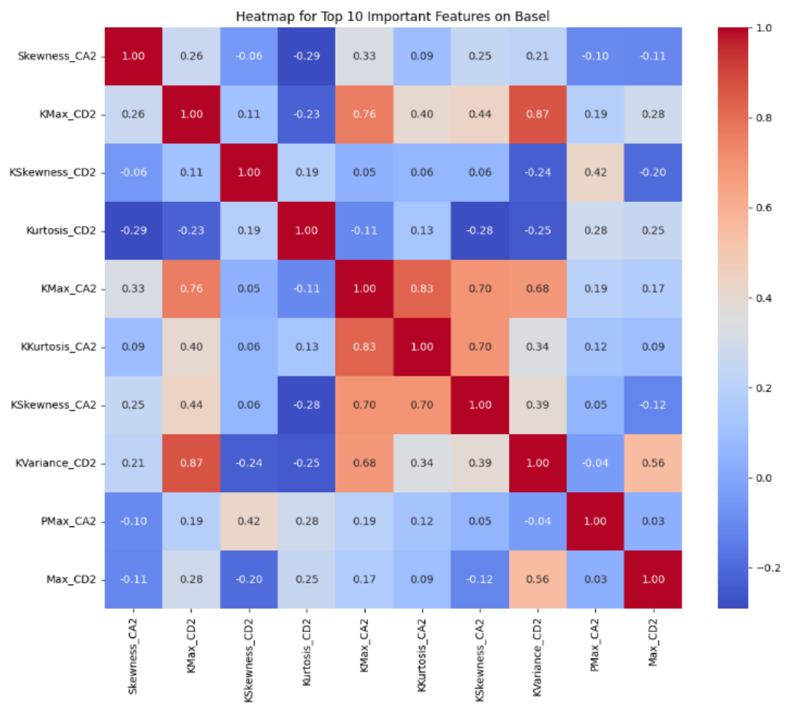

Figure 17. Correlation between important features and health status

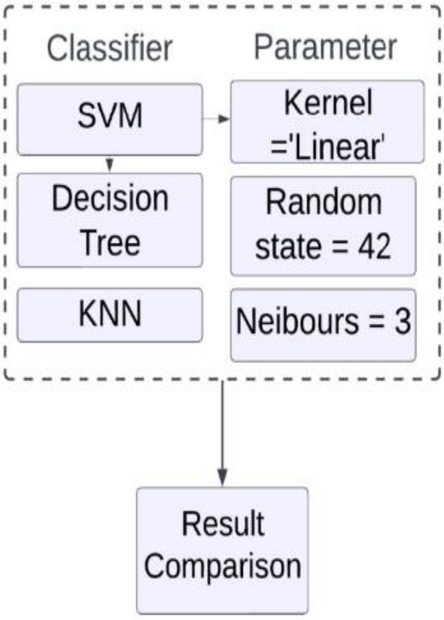

Figure 18. Classifiers with Specific Parameters

5. Results and Discussion

6 filtering techniques are implemented and 60 features which were extracted, given to the classifiers and the results are obtained, which are discussed below.

5.1 Filter Performance

The efficiency of the filter is determined using three techniques. This will help to assess the performance of various filters.

5.1.1 Signal-to-noise Ratio (SNR)

It is the relation between signal strength and present noise. The higher the SNR value indicates superior denoising performance.

$$SNR = 10 \cdot log_{10}\left(\frac{\sum_{p=1}^{N} x_{original}[p]^2}{\sum_{p=1}^{N}\left(x_{original}|p| - x_{denoised}|p|^2\right)}\right) \quad (14)$$

Where, $x_{denoised}|p|$ = denoised signal of sample p

N = Number of samples.

5.1.2 Mean Square Error (MSE)

which is the mean squared difference between the original signal and the denoised signal. Denoising performance improves with drop is MSE value. MSE = 0 indicates perfect match between original & denoised signal.

$$MSE = \frac{1}{N}\sum_{1=1}^{N}\left(x_{\substack{Signal\\ original}}[i] - x_{denoised}[i]\right)^2 \quad (13)$$

Table 1 displays the sample MSE and SNR values for moving average filter grouped according to health issue and gender. These values show the overall significant change when collected from healthy and non-healthy subjects. Further keen investigation may help in using these values to classify the subjects.

Table 1. MSE and SNR values for Basel Filter

Health Issue	Gender	MSE	SNR
No	F	0.48971	62.46499
No	M	0.38567	62.67369
Yes	F	4.16329	60.48799
Yes	M	0.46891	62.99434
No	Overall	0.43769	62.56934
Yes	Overall	2.52134	61.60192

5.2 Classifier Performance

For checking the accuracy according to the filter technique used, the same samples were checked for each filter type. Each classifier's performance was measured using metrics such as accuracy, precision, recall, and F1-score to ensure a thorough assessment. Among the classifiers, KNN demonstrated superior performance in handling the high-dimensional and non-linear characteristics of the pulse signal dataset, achieving the highest accuracy when used with Butterworth filter. The Decision Tree model provided interpretable results while used with Basel filter. KNN's performance was highly dependent on the choice of k and was sensitive to noise in the data. These findings underscore the potential of classifiers for accurate pulse signal classification while identifying areas for improvement in all classifiers used with other filters, paving the way for further enhancement in sensor-based pulse diagnosis systems. Each filter's efficiency was assessed based on its ability to improve signal quality and improve classification correctness.

5.2.1 According to number of features extracted

The results obtained are discussed further in this section. Charts in figure 19 (a-c) provide a thorough assessment of the classifiers' performance on the median filter across three feature domains: frequency domain (24 features), wavelet domain (36 features), and the combined domain (60 features). The performance metrics, which includes accuracy, precision, recall, and F1-score, emphasize that every domain contributes to the classifiers' efficacy in investigating pulse signals. The spectral (signal periodicity and harmonics) information, which is captured by frequency domain demonstrate moderate performance. On a contrary, localized pattern and subtle variations which are identified by wavelet domain leads to improved performance metrics. Whereas the combined domain leads to highest performance across all classifiers. It combines the strength of frequency and wavelet domain leading to improved accuracy and robustness. Thus, selecting the proper feature set drives towards optimized classification performance of automated Nadi Pariksha system.

5.2.2 According to the filters used

Charts in figure 20 (a-c) revels the classifier evaluation metrics for all 6 filters in terms of accuracy, F1 score, and recall, precision. The evaluation evidently exhibits the better performance of Moving average filter combined with DT and Butterworth filter combined with KNN. Moving average filtered data achieves 92% accuracy with DT and Butterworth filtered data attains 92% accuracy with KNN. Median filtered data exhibits consistent performance for all classifiers.

Chart in figure 21 shows the primary accuracy comparison of all filters and classifiers. Corresponding table 2 exhibits the numeric data for accuracies attained by these filters.

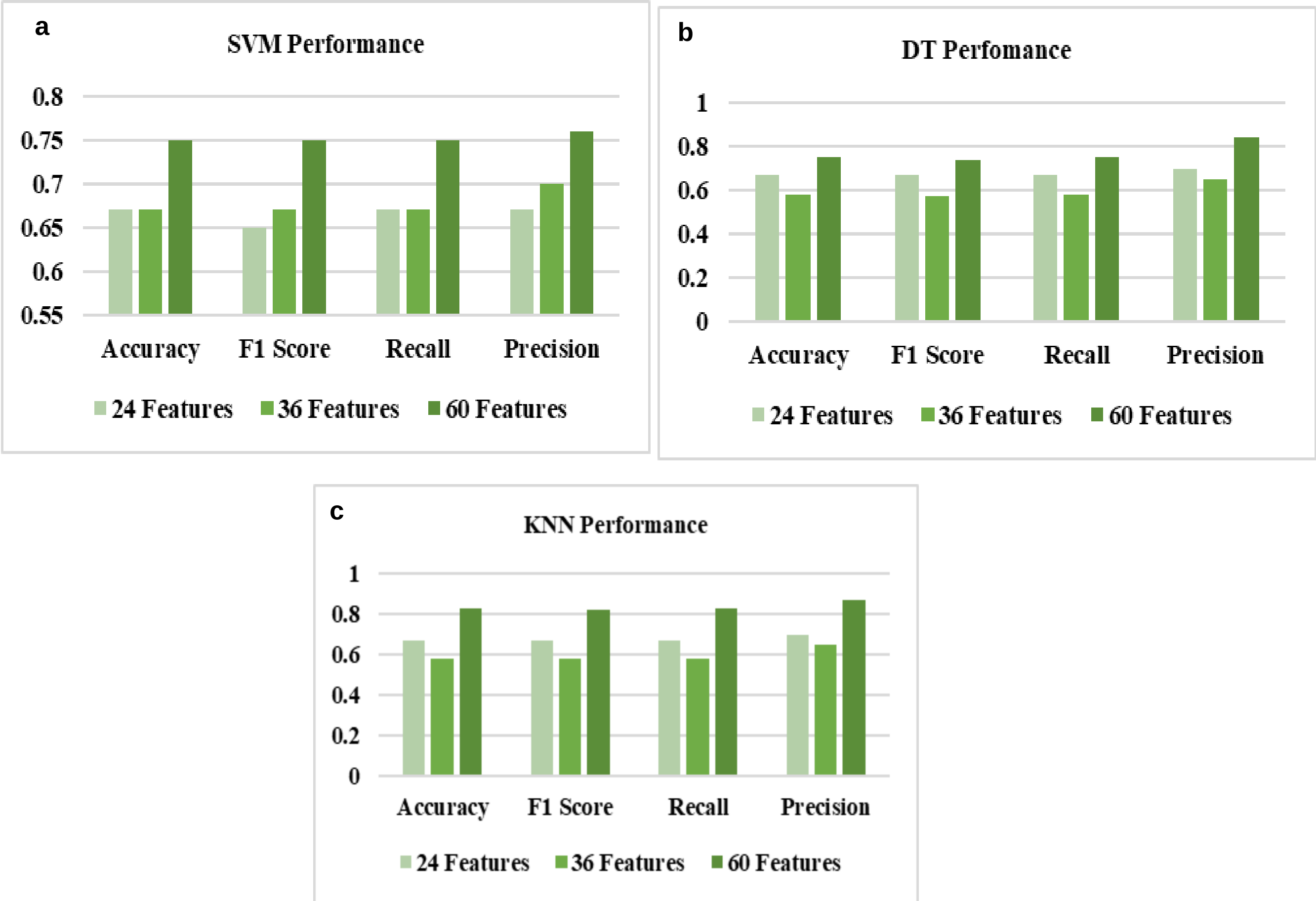

Figure 19a. Median Filter with SVM Classifier, **b**. Median Filter with DT Classifier, **c.** Median Filter with KNN Classifier

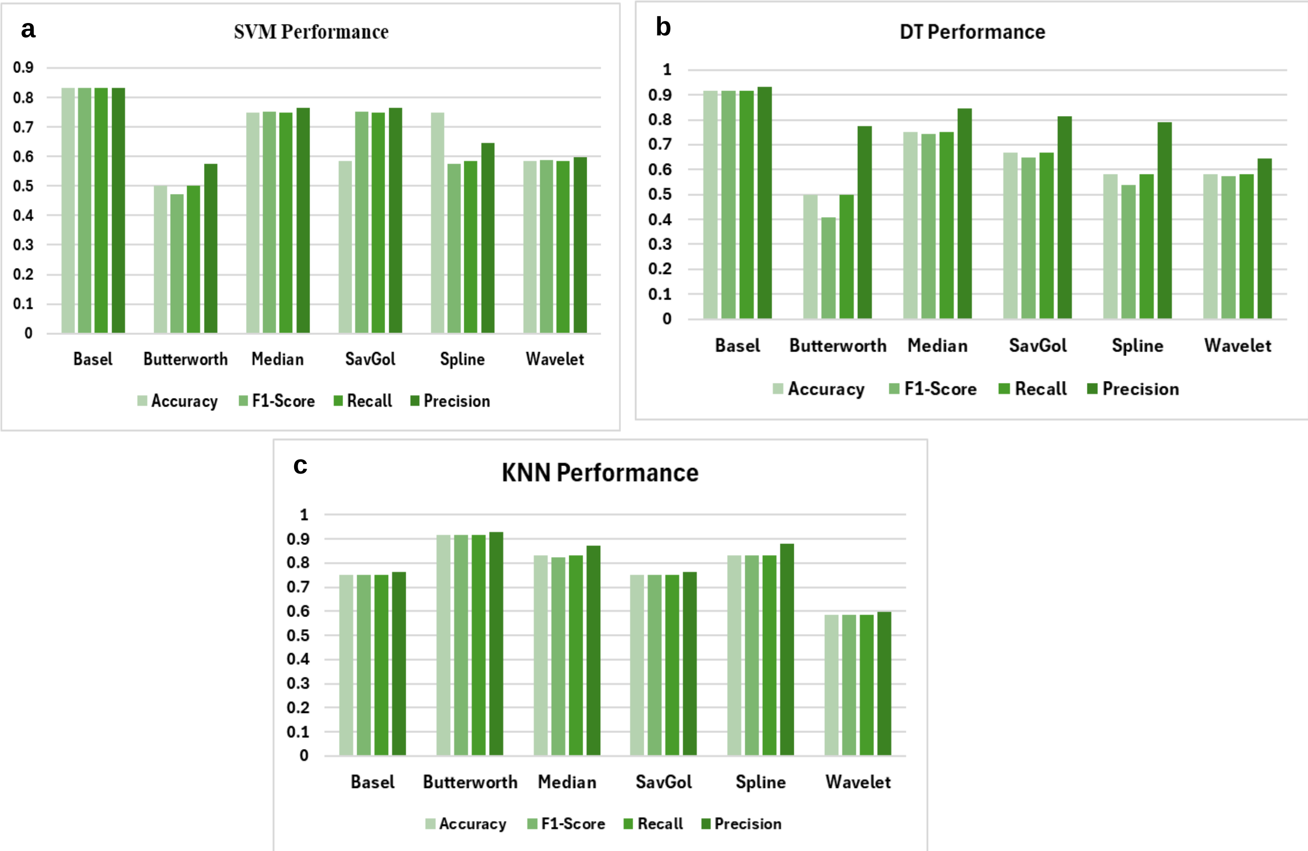

Figure 20a. SVM Classifier on all filters Performance, **b.** DT Classifier on all filters Performance, **c.** KNN Classifier on all filters Performance

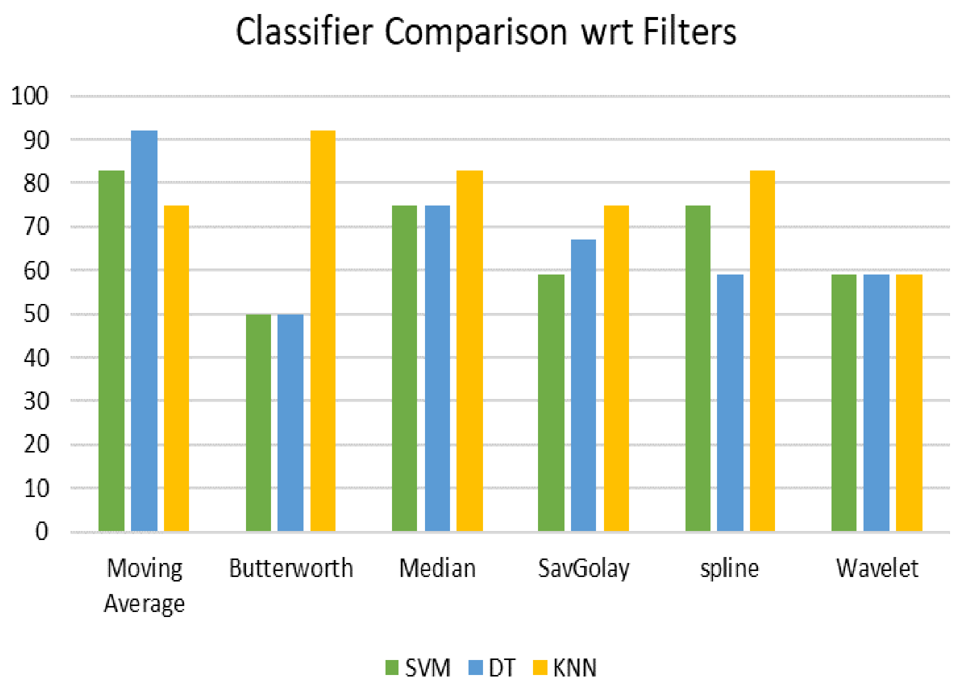

Figure 21. Filters and Classifier Accuracy

Table 2. **Accuracy with respect to Filter Type**

Filter/Accuracy	SVM	DT	KNN
Basel	83	**92**	75
Butterworth	50	50	**92**
Median	75	75	83
SavGol	59	67	75
spline	75	59	83
Wavelet	59	59	59

Table 3. Performance comparison for Indian authors in healthcare domain

Sr. No	Sensor Used	Features	Feature extraction	Disease diagnosed	Classifier	Results %	Reported in
Indian Authors in Healthcare (Nadi Pariksha (Pulse Diagnosis)) domain							
1	Pulse		Spectral analysis Bessel and Butterworth filter	VPK	Statistical Analysis	Comparison of 2 filters	[11]
2	Pressure sensor	Percussion Peak	Wavelet based techniques Non-linear Poincare analysis	autonomic nervous system	Statistical Analysis	Verified	[22]
3	PPG Sensor	rising and falling peaks	Butterworth	VPK identification	Statistical Analysis	Compared with theoretical knowledge	[26]
4	Pulse sensors	Peak Difference	Mean for VPK	VPK Dominance	Statistical Analysis	Verified with daytime	[63]
5	Optical pulse sensor	10 Pulse features based on pulse amplitude	FFT, power spectrum graphs pattern recognition methods	Cold fever back pain pregnancy	KNN, SVM LDA, QDA, DT	90.9% 79.8%	[69]
6	Pressure transducers	BMI, Systolic and diastolic BP	-	Diabetes	Statistical Analysis	P values are calculated	[70]
7	Pulse	60 features	Time domain, frequency domain, 1D DWT, 6 filters	Healthy vs non-Healthy	KNN, DT, SVM	92%	Proposed system
Indian Authors in Healthcare (other than Nadi Pariksha) Domain							
8	Kermany Dataset Image processing	Image features	3x3 convolutions	Paediatric Pneumonia	CNNs Transfer Learning Based Ensemble Models	98	[29]

9	Heart disease dataset	11 features	Pearson's coefficient (PCC)	Cardiovascular	ML & DL based stacked (DNN, ML, KDNN ensemble model	89.65	[30]
10	ECG beats dataset, ICEEMD + (HOS, sample entropy)	ECG features	Hinich test, adaptive nonlinear decomposition	Classification of imbalanced ECG beats	re-sampling AdaBoost ensemble	96.5 SEN, 99.1 SPE, 99.5 ROC, 98.6 ACC	[32]
11	Sound analysis from Dataset	Sound features	Band Filter Down Filtering	Heart Disease	RNN, LSTM	71.2	[71]

Table 3 gives a listed relative breakdown of research conducted by different Indian authors in the realm of Nadi Pariksha. These studies use pulse (Nadi) signals to assess both specific diseases or the Tridoshas like Vata, Pitta, and Kapha and show up their physiological and investigative importance. The table point out the variety of attempts, ranging from conventional methods to advanced signal processing and machine learning techniques, to investigate the Nadi (pulse) waveforms. Previous researchers have used R, SPSS, Excel, and MATLAB as standard statistical tools to predict results using statistical operations [1, 11, 26, 63]. Researchers have also used the standard neural network, Machine learning algorithms to get the results predicted [31, 40, 48]. Both heart disease, lung cancer and VPK analysis in the human body are predicted through the research.

Each study deals with some of the important sides, such as the role of pulse signals in studying dosha imbalances, identifying chronic diseases, or comparing Nadi (pulse) parameters with medical investigational reports.

This will also unfold the way towards future work meant to develop robust frameworks and incorporating progressive technologies to grow the predictive ability of Nadi Pariksha in contemporary healthcare.

6. Conclusion

Optical sensors are pretty good sensors to sense the weak *Nadi* signal. Their performance is decent in most of the situations. Recently many studies are carried out to understand the *Nadi* Signal. According to traditional knowledge wrist is the most suitable body location to collect *Nadi* signal. It is observed that data set collection is a major challenge. It is possible to collect the data of arterial pulse or Nadi signals effectively by the study device designed with three sensors, ADC, and microcontroller. The data analysis & diagnosis of health conditions according to traditional *Ayurveda* knowledge theory is performed. This study focuses on the performance of filtering techniques and found that Moving average and Butterworth filters when employed respectively with DT and KNN gives better results. Whereas KNN performs constantly better with all types of filters. It is also observed that age and gender of the subject contributes to the health status of the subject. The huge dataset if created will help in improving the accuracy of the study. Working with specific disease diagnosis, as well as *Prakriti Parikshan* according to the *Ayurvedic* literature is also a future task. CNN models and deep learning model is also a challenge which requires a huge data set. Ultimately improving the diagnostic accuracy is the aim of proposed work.

The conclusions of this study have noteworthy real-world applicability, predominantly in the automation of Nadi Pariksha for contemporary healthcare. By employing cutting-edge sensors, advanced machine learning algorithms, and real-time analytics, the computerised system transforms traditional pulse diagnosis into an inflatable and accurate diagnostic instrument. This automation improves accessibility, particularly in rural and remote areas, providing a cost-effective solution for preventive healthcare and timely rather early diagnosis. Its acquaintances the gap between traditional Ayurvedic practices and modern evidence-based medicine.it proposes a harmonising approach that keeps the spirit of Ayurveda while improving accuracy and usability. Additionally, the system's potential amalgamation with wearable devices and mobile applications enables continuous health monitoring and personalized wellness recommendations, encouraging a transformative change towards technology-driven, all-inclusive healthcare solutions.

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Authors Contribution Statement

Mrunal Fatangare- Conceptualization, Methodology / study design, Data collection, Formal data Analysis, Writing original draft, Writing—review & editing. Dr. Sukhada Bhingarkar -Conceptualization, Supervision, Validation, Writing - review & editing. All authors read and approved the final manuscript.

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Competing Interests

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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