DISEASE DIAGNOSIS WITH WRIST PULSE SIGNAL USING MACHINE LEARNING (VAATA, PITTHA, KAPHA)

A PROJECT REPORT

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in partial fulfillment for the award of the degree

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BONAFIDE CERTIFICATE

This is to certify that this project entitled **"DISEASE DIAGNOSIS WITH WRIST PULSE SIGNAL USING MACHINE LEARNING (VAATA, PITTHA, KAPHA)"** submitted by

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EXTERNAL EXAMINER

Abstract

Ayurveda, which means "the science of life," is rooted in the belief that the universe is composed of five fundamental elements: fire, water, air, earth and ether. These elements are associated with the five senses of the human body, and they form the basis of Ayurvedic principles. Additionally, they are linked to the three Doshas: Vaatha, Pittha, and Kapha. The balance of these elements and Doshas is crucial for maintaining good health, according to Ayurveda.

Nadi Pariksha is the ancient ayurvedic technique of diagnosis through pulse, using these Ayurveda technique it checks the presence of disease in our human system will be indicated as an imbalance in our 'doshas'. A person with vaata predominant people have quick mind, flexibility and creativity, pittha people have warm bodies, penetrating ideas and sharp intelligence, kapha people have strength, endurance and stamina. When these doshas are imbalanced there are some abnormalities too.

The labeled dateset consists of 1071 samples with 31 features like acidity, headache and indigestion. It has target disease the patient is associated with that includes Migrane, Arthrisis, Diarrhea and Gastrisis. The dataset is divided into 80 and 20 percentage for training and testing respectively. The number of features are minimized to 16 using Principal Component Analysis (PCA). The Machine learning algorithms such as KNN, XGboost, and decision trees are considered for classification of diseases. It is observed that the Decision tree is the best algorithm. After testing and training the model can identify what disease a patient is associated with by the help of 13 features as input that is whether a patient is associated with headache, indigestion or acidity and so on.

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LIST OF ABBREVIATIONS

ANN Artificial Neural Network

DCNN Deep Convolutional Neural Network

DT Decision Tree

KNN K Nearest Neighbor

NB Naives Bayes

PPG Photoplethysmography

RMSE Root Mean Square Error

SEEHT Shannon Energy Envelope Hilbert Transform

SVM Support Vector Machine

TCM Traditional Chinese Medicine

WPS Wrist Pulse Signal

Chapter 1

INTRODUCTION

1.1 Introduction to Ayurveda

Ayurveda, an ancient medicinal science, started in the Indian sub-continent. Ayurveda defined as the ”science of life”, where it promotes overall well-being by ensuring a harmonious equilibrium between the body, mind, and spirit. In our contemporary technological society, every individual is ensnared by illness throughout the initial phases of life, thus it becomes imperative to acquire knowledge regarding the optimal means of maintaining good health. Ayurveda is a discipline that teaches about the balance of nature and how to restore balance when it is disrupt where it establishes a correlation between the utilization of the senses and the occurrence of ailments. Misapplication of the senses results in discordance between humanity and the natural world, or an in equilibrium within human character. The principle of Ayurveda is based on the fundamental equality between nature and self. An individual who embraces Ayurveda as a way of life is more likely to lead a healthy existence devoid of ailments by adhering to the principles and guidelines of Ayurveda.T In Ayurveda, the natural universe is composed of five fundamental elements known as Pancha Mahabhutas. The five elements of Ayurveda can also be associated with various aspects of human awareness.

1.2 Panchamahabhutas and Tridosha

In Ayurveda, there are five great elements which are attributed to different human consciousness. The first element amongst them is ‘ether’, then ‘air’,‘fire’,‘water’,and finally ‘earth’.

The five great elements combine together to form as a ‘Dosha’, which forms the overall constitution. There are 3 Doshas - Vaata, Pittha and kapha, which are predetermined from the moments of the conception as shown in figure 1.1.

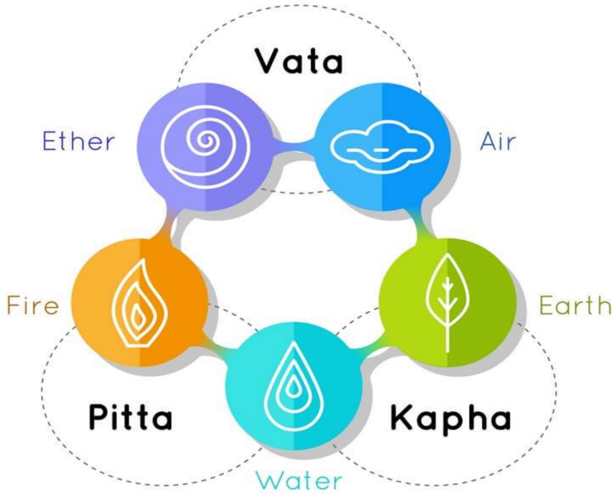

Fig. 1.1: Five elements and Tridoshas

There are totally eight pulse positions in human body, and wrist hand position consider as main. For Vaata - ring finger, for Pittha – middle finger, for Kapha – index finger. The Vaata pulse rate is 80 – 100 bpm, Pittha pulse rate is 70 - 80 bpm, and the Kapha pulse rate is 60 – 70 bpm. We know that each elements are interconnected and if one element is disturbing, it can affect the other elements, similarly one abnormality in human body can affect other disorders too. In humans, the pulse in males are taken in right hand wrist, and in females the pulse are taken in left hand wrist. Each wrist has three pulse postions, i.e., vaata, pittha, kapha, totally six positions and these six positions connected to twelve body organs, i.e., one pulse position responds to two body organs.

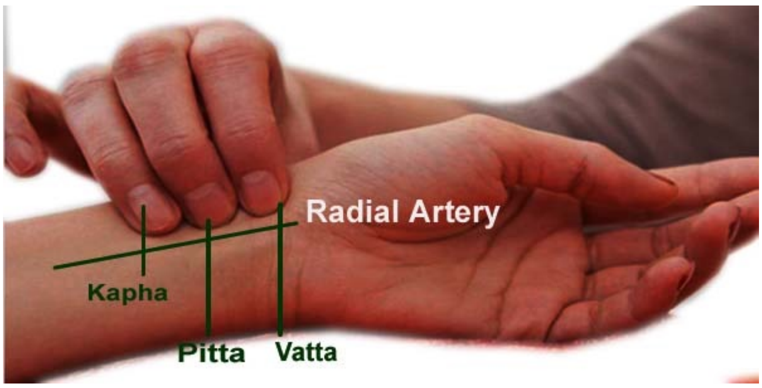

Fig. 1.2: Tridoshas positions in wrist hand

1.2.1 Vaata Dosha

A mixture of ether and air forms vaata. Its main principles are movement and flow. Humans with this dosha are usually described as slim, energetic, and creative. They have abilities to learn quickly, highly creative minded, and kind - hearted. But they do have some disabilities like unconscious mind, unstable mood, highly sensitive to cold, trouble in sleeping, irregular appetite and eating pattern.

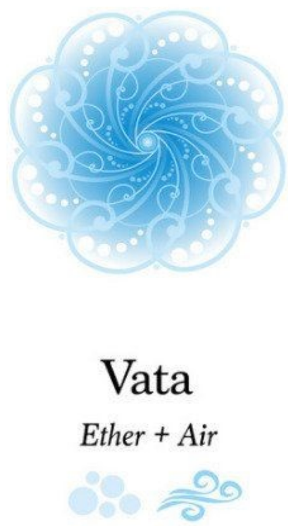

Fig. 1.3: Vaata Dosha and its elements

1.2.2 Pittha Dosha

Water and fire combine to form Pittha. Pittha's primary characteristic is transformation. Humans with this dosha are usually described as muscular build, and be very athletic. They have abilities to be as natural leaders, self - determined, intelligent and purposeful. But they do have some disabilities like being impatient, always hungry, mood swings, sensitive to hot temperatures.

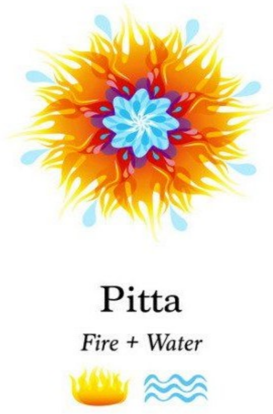

Fig. 1.4: Pittha Dosha and its elements

1.2.3 Kapha Dosha

Kapha is formed from earth and water elements. It provides the body with its major protection against movement (Vaata) and excessive heat (Pittha). Humans with this dosha are usually described as strong, thick - boned and caring person. They have abilities like being as a caring, trusting, patient and calm person, with strong bones and joints, and healthy immune system. But they do have some disabilities like having slow metabolism, breathing issues like asthma, over - sleeping, higher risk of heart - disease, depression, and need regular motivation.

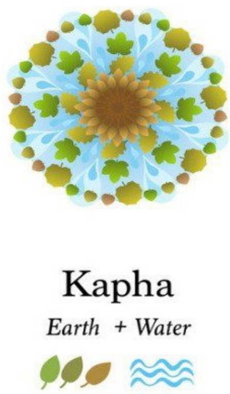

Fig. 1.5: Kapha Dosha and its elements

1.3 Literature Review

The research study aims to utilize machine learning algorithms to predict human body constituents, namely Ayurveda Dosha. The data are obtained from 1071 samples who were in abnormal conditions. The data was trained and tested using a range of machine learning techniques, including K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Decision Tree (DT), XGBoost, and Logistic Regression. The study also compared other performance measures such as accuracy, precision, recall, and F-score across the different models. The findings suggest that machine learning algorithms effectively predict human body constituents and may have potential applications in the field of Ayurvedic medicine. [1].

This study is to identify the disease from Ayurvedic pulse diagnosis using Nadi Pariksha. An innovative Photoplethysmography (PPG) heart rate sensor interfaces with Arduino to collect wrist pulse signals. The average value of the signal is calculated from each sample, to identify which Dosha abnormality the sample patient does have? and with what range of abnormal heartrate? and according to the range, what type of symptoms do the patient have?. After collecting every information or data collected, we can use the Machine Learning Model to identify, the dosha and the disease caused from the sample using the features. [2].

This research study discusses the use of pulse diagnostics in Ayurveda to determine the underlying cause of ailments and disorders. The process of diagnosing a pulse requires sensation of the wrist's radial artery with the tip of the finger. The study emphasizes the strong connection between the heart and mind as well as the significance of wrist pulse signals (WPS) in assessing the physiological state of the complete human body. The study examines the application of WPS analysis to map human emotions with diseases based on the inherent imbalance of Vaata, Pitta, and Kapha. Emotions are important indicators of an individual's mental state. The study also highlights the need for more research in this field and explores the possibility of utilizing WPS for emotion recognition. Overall, the research paper emphasizes the significance of pulse diagnosis in understanding and diagnosing various physical and mental ailments.[3].

This study suggests creating a system for early human health diagnostics using conventional Ayurvedic techniques. The goal of the research is to help physicians diagnose conditions like hypotension, gastritis, and asthma by developing a minimally intrusive tool and questionnaire. The traditional Ayurvedic method of pulse examination, known as Nadi Pariksha, is utilized for diagnosing ailments. The pulse signals, representing Vata, Pitta, and Kapha, are examined to diagnose various diseases. The system combines pulse examination, questionnaire responses, and analysis of cough, eyes, and face to generate a prescription for the diagnosed disease. The study also discusses the use of machine learning algorithms for analyzing pulse signals and predicting disorders. The proposed system aims to provide convenient and accurate diagnoses based on ancient Ayurvedic techniques combined with modern technology.[4].

This study focuses on the Traditional Chinese Medicine Pulse Diagnosis, specifically the identification of wrist pulse signals. In order to enhance the recognition impact, the authors suggest a new methodology that combines the use of Deep Convolutional Neural Networks (DCNN), Shannon Energy Envelope, and Hilbert Transform (SEEHT). The study illustrates the efficiency of the pulse wave extractor SEEHT, which works better than conventional techniques when dealing with broader pulse waves or sharp amplitude oscillations. To expand the sample size and extract possible features, additional noise is added during the DCNN's training process. The paper emphasizes the need for standardizing and objectifying pulse diagnosis methods through computer-aided analysis.[5].

Along with discussing earlier studies on pulse diagnosis, the report suggests future study directions. All things considered, this technique has promise for non-invasive disease diagnostics. The study highlights the shortcomings of conventional pulse diagnosis techniques in conventional Chinese medicine and suggests a novel way to increase pulse signal acquisition's precision and effectiveness. The authors point out that the majority of traditional pulse signal collection tools are only able to record signals at a single location and with a single pressure, which restricts the quantity of diagnostic data that can be gathered. The authors suggest a compound system for multichannel pulse signal acquisition that incorporates mechanical structure design, pressure adjustment, sensor array design, and sensor positioning in order to solve this problem. With the system's ability to record pulse signals at various pressures and places, the patient's health status can be represented more thoroughly and accurately.The authors show that, as compared to single-channel signals, multichannel pulse signals perform better in classification.[6].

This study investigates the application of pulse signal analysis in Ayurvedic medicine for disease diagnosis. The authors created the Nadi-Pariksha system, which uses wrist pulse signals to diagnose illnesses. This approach seeks to address shortcomings in conventional diagnosis techniques by utilising the pulse signal, which provides important information about the body. The hardware for recording the pulse signal consists of a low-pass filter, amplifier, and microphone sensor. Support vector machines are utilised for classification, and auto correlation and the Fast Fourier transform are employed to extract features. The results of the trial demonstrated a promising accuracy of 88.8 for pre-meal signals and 81.48 for post-meal signals in determining whether or not an individual had consumed.Along with discussing earlier studies on pulse diagnosis, the report suggests future study directions. All things considered, this technique has promise for non-invasive disease diagnostics. [7].

This work describes an algorithm that uses photoplethysmography (PPG) to track blood flow and detect the direction of the pulse. This method is intended to be applied with a wrist band. PPG is commonly used in medical equipment for a variety of reasons; however, noise and motion artefacts can cause interference. However, the majority of previous research has focused on reducing these abnormalities. In this research, a method that efficiently detects the direction of PPG pulses without requiring wrist movement is presented. This technique is essential to developing fast and accurate PPG pulse direction recognition for continuous monitoring, independent of body motions. The authors also go over the shortcomings of the wrist band devices that are currently in use, which usually only measure PPG on the dorsal side of the wrist. They created a band gadget that monitors blood flow on a radial artery branch that is situated at the wrist, close to the thumb's extensor tendons. The application of PPG for quantitative cardiovascular parameters is advanced by this study. [8]

The analysis of wrist pulse waveforms in Traditional Chinese Medicine (TCM) engineering and diagnosis modernization is the main topic of this research article. The technique for automatic time-domain feature extraction of the pulse waveform is proposed in this study and is based on derivatives. The extracted features are subjected to variability analysis, and the variability of the features is subjected to cross-correlation analysis to minimise the pattern's dimension. Along with evaluating the classification performance of reduced features and different feature combinations, the paper also gives a genuine classification case study. The study's dataset consists of the pulse waveforms of fifty patients with cardiovascular disease and twenty healthy people. The outcomes demonstrate that the features chosen are appropriate and that the classification performance is satisfactory. The overall goal of the paper is to identify a workable method for pattern dimension reduction and time-domain feature extraction in wrist pulse waveform analysis. [9].

The study paper suggests a workable technique for dividing the wrist pulse waveform into segments and figuring out the average waveform. Important factors that may impact how well these activities are performed are addressed by the writers. To handle high-frequency noise and low-frequency fluctuations without distortion, they employ zero-phase filtering. To guarantee precise segmentation, they additionally use a moving-window adaptive threshold segmentation technique. The work presents a number of methods, such as average waveform estimation, cross-covariance-based alignment, outlier removal, and waveform rotation and scaling. The results of the testing show how effective the segmentation performance was, with the average waveform that was produced exhibiting the usual features of the wrist pulse trend. While acknowledging earlier waveform segmentation techniques, the study also points out that not all important factors that can lead to poor segmentation performance have been studied in depth.[10].

1.4 Objectives

For Disease Diagnosis for Wrist Pulse Signal using Machine Learning following tasks are considered as objectives:
1.To train the machine learning algorithm to identify diseases in individuals, we employ a variety of methods including Decision Trees, X G Boost, Support Vector Machines, Logistic Regression, and K-Nearest Neighbors, utilizing a labeled dataset.
2.To classify dataset into four classes

- Migraine
- Arthritis
- Diarrhea
- Gastritis

3.Predicting the Output of given input using the Trained Model.
4.Verifying the output based on Photoplethysmography based Heart Rate Sensor.

1.5 Report Outline

This report consists of this introductory chapter and other chapters arranged as below:
Chapter 1 Gives about the Introduction about Ayurveda, Tridoshas, and Literatue Survey.
Chapter 2 Gives a detailed description of components used.
Chapter 3 Datatset details provided and Data pre-processing for the dataset has done.
Chapter 4 Usage of the evaluation metrics of the dataset from various machine learning models

is measured.

Chapter 5 Extraction of the best features using feature extraction methods.

Chapter 6 Experimental verification by using Photoplethysmography Heart Rate Sensor.

Chapter 7 Conclusion and Future Scope has been outlined.

Chapter 2

COMPONENTS USED

2.1 Photoplethysmography sensor

Photoplethysmography is a simple and inexpensive optical sensor to measure volumetric changes in peripheral blood flow by using a light source and a photo detector by placing at the skin's surface.

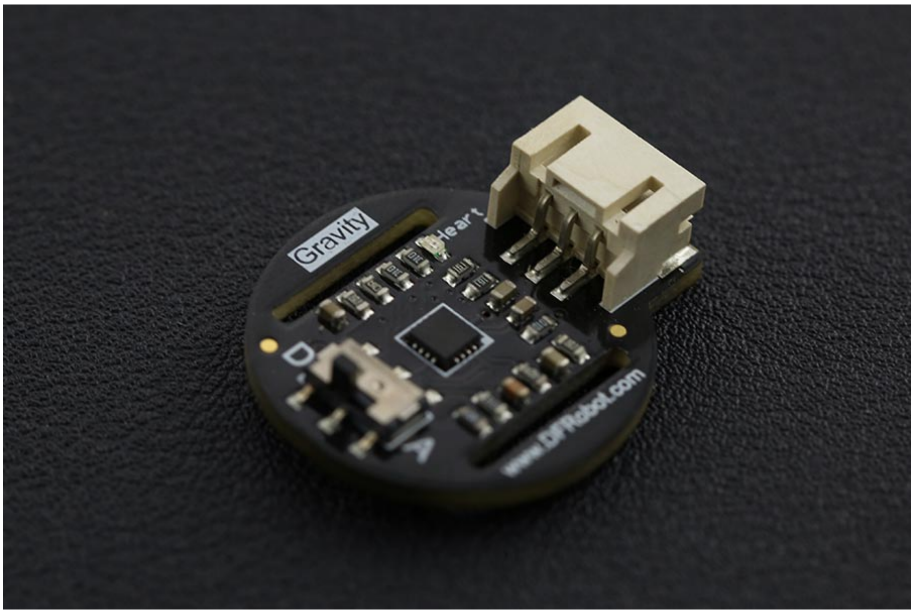

Fig. 2.1: PPG sensor

2.2 Arduino UNO

In the setup for wrist pulse measurement, the Arduino Uno microcontroller plays a pivotal role. This versatile device connects to the PPG sensor, acquiring the data generated by the sensor's measurement of blood volume changes in the wrist. The Arduino Uno's capabilities extend to data processing, enabling tasks such as signal filtering, peak detection, and waveform analysis. Moreover, it can be programmed to output the processed data to external devices or interfaces, making it the central component in non-invasive heart rate monitoring setups.

Arduino Uno's flexibility and ease of use make it a popular choice for projects like this, offering a robust platform for collecting and processing physiological data with a PPG sensor, contributing significantly to healthcare and wellness applications.

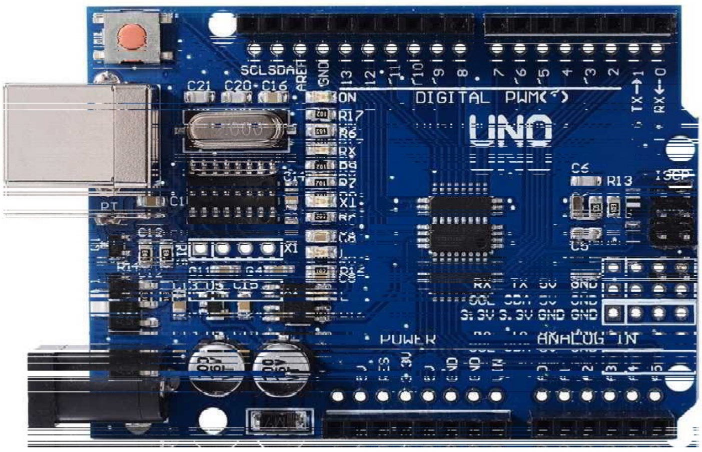

Fig. 2.2: Arduino UNO

2.3 Project Block Diagram

Fig. 2.3: Block Diagram - Hardware

Chapter 3

DATASET

3.1 Feature Description

1. **Acidity:**The person is having acidity (0 = false; 1 = true)
2. **Indigestion:** The person is having indigestion (0 = false; 1 = true)
3. **Headache:** The person is having headache (0 = false; 1 = true)
4. **Blurred and Distorted Vision:** The person is having acidity (0 = false; 1 = true)
5. **Excessive hunger:** The person is having excessive hunger (0 = false; 1 = true)
6. **Muscle weakness:** The person is having muscle weakness (0 = false; 1 = true)
7. **Stiff neck:** The person is having stiff neck (0 = false; 1 = true)
8. **Swelling joints:** The person is having swelling joints (0 = false; 1 = true)
9. **Movement stiffness:** The person is having movement stiffness (0 = false; 1 =true)
10. **Depression:** The person is having depression (0 = false; 1 = true)
11. **Irritability:** The person is having irritability (0 = false; 1 = true)
12. **Visual disturbances:** The person is having visual disturbances (0 = false; 1 = true)
13. **Painful walking:** The person is having painful walking (0 = false; 1 = true)
14. **Abdominal pain:** The person is having acidity (0 = false; 1 = true)
15. **Nausea:** The person is having acidity (0 = false; 1 = true)
16. **Vomiting:** The person is having vomiting (0 = false; 1 = true)
17. **Blood_in_mucus:** The person is having Blood in mucus (0 = false; 1 = true)
18. **Fatigue:** The person is having fatigue (0 = false; 1 = true)

19. **Fever:** The person is having fever (0 = false; 1 = true)

20. **Dehydration:** The person is having dehydration (0 = false; 1 = true)

21. **Loss_of_appetite:** The person is having loss of appetite (0 = false; 1 = true)

22. **Cramping:** The person is having cramping (0 = false; 1 = true)

23. **Blood_in_stool:** The person is having blood in stool (0 = false; 1 = true)

24. **Gnawing:** The person is having gnawing (0 = false; 1 = true)

25. **Upper_abdomen_pain:** The person is having upper abdomen pain (0 = false; 1 = true)

26. **Fullness_feeling:** The person is having fullness feeling (0 = false; 1 = true)

27. **Hiccups:** The person is having hiccups (0 = false; 1 = true)

28. **Abdominal_bloating:** The person is having abdominal bloating (0 = false; 1 = true)

29. **Heartburn:** The person is having heartburn (0 = false; 1 = true)

30. **Belching:** The person is having belching (0 = false; 1 = true)

31. **Burning_ache:** The person is having burning ache (0 = false; 1 = true)

32. **Type of dosha:** The person is vaatha, pittha, and kapha.

33. **Prognosis:** The person is having migraine, arthritis, diarrhea, and gastritis.

3.2 Major Features affecting the Disease Diagnosed

3.2.1 Migraine:

- **Visual disturbances:** due to headache, visual processing is disrupted.
- **Stiff Neck:** tends to muscle tension in neck area, causing stiffness.
- **Irritability:** fluctuation in brain leads to mood swings and emotional problems.
- **Indigestion:** triggering the digestive system, leads to indigestion.
- **Excessive hunger:** occurred due to change in appetite.

3.2.2 Arthritis:

- **Muscle weakness:** caused due to inflammation and pain in muscles.
- **Stiff Neck:** caused due to inflammation and pain in neck muscles, leads to discomfort to move the head.
- **Movement stiffness:** caused due to inflammation and pain in joints, difficult to move.
- **Painful walking:** causing inflammation and pain by putting pressure on the joints.
- **Swelling Joints:** the inflammation can cause the joints to produce fluid.

3.2.3 Diarrhea:

- **Nausea:** arises due to irritation and inflammation in digestive tract.
- **Blood in mucus:** caused to inflammation or damage to lining of digestive tract.
- **Cramping:** caused due to contractions of intestinal muscles.
- **Fever:** manifested due to low immune response in the body.
- **Vomiting:** caused due to expel of irritants or toxins from the digestive tracts.

3.2.4 Gastritis:

- **Indigestion:** arises from inflammation of stomach lining, disrupts normal digestion.
- **Abdominal pain:** caused by inflammation and irritation of stomach lining.
- **Hiccups:** inflammation of stomach lining irritates a nerve, which controls diaphragm, sudden contractions of diaphragm leads to hiccups.
- **Fullness Feeling:** inflammation of stomach lining, interfere with normal emptying of stomach, causing a sensation of fullness without having large meal.

3.3 Methodology

3.3.1 Data Collection:

The Dataset collected has been classified based on the disease diagnosed, and later classified based on the dosha, for the respective disease.

3.3.2 Data Cleaning:

Rectifying missing values, eliminating duplicate records, and mitigating data inconsistencies.

3.3.3 Data Transformation:

The Dataset consists of object feature data type, is transformed into numerical feature data types.

3.3.4 Methods used for data transformation:

- Replace technique
- Using the label encoding technique, object data types are transformed into numerical ones so that machine learning models that require only numerical input can be fitted.

3.4 METHODOLOGY BLOCK DIAGRAM

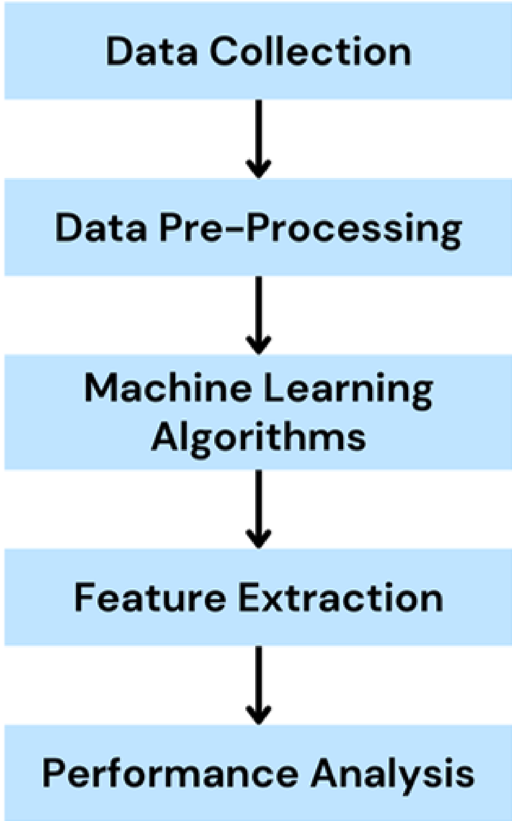

Fig. 3.1: Block-Diagram

3.5 Data Preprocessing

The process of cleaning and modifying data to make it ready for analysis is known as data pre-processing. Pre-processing data aims to make it consistent, dependable, and ready for analysis. It helps to improve the calibre and efficiency of the data mining procedure.

3.5.1 Information of features data type and null values

Understanding the data types of features and handling null values are essential for effective pre-processing in data analysis and machine learning tasks. Data types provide critical information about the nature of features, guiding preprocessing steps such as encoding categorical variables, scaling numerical features, or tokenizing text data. Meanwhile, identifying and addressing null values are vital for maintaining data integrity and preventing bias in analyses.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1071 entries, 0 to 1070
Data columns (total 22 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   acidity                      1071 non-null   int64 
 1   indigestion                  1071 non-null   int64 
 2   headache                     1071 non-null   int64 
 3   blurred_and_distorted_vision 1071 non-null   int64 
 4   excessive_hunger             1071 non-null   int64 
 5   muscle_weakness              1071 non-null   int64 
 6   stiff_neck                   1071 non-null   int64 
 7   swelling_joints              1071 non-null   int64 
 8   movement_stiffness           1071 non-null   int64 
 9   depression                   1071 non-null   int64 
 10  irritability                 1071 non-null   int64 
 11  visual_disturbances          1071 non-null   int64 
 12  painful_walking              1071 non-null   int64 
 13  abdominal_pain               1071 non-null   int64 
 14  nausea                       1071 non-null   int64 
 15  vomiting                     1071 non-null   int64 
 16  blood_in_mucus               1071 non-null   int64 
 17  Fatigue                      1071 non-null   int64 
 18  Fever                        1071 non-null   int64 
 19  cramping                     1071 non-null   int64 
 20  type of dosha                1071 non-null   object
 21  prognosis                    1071 non-null   object
dtypes: int64(20), object(2)
memory usage: 184.2+ KB
```

Fig. 3.2: Data type and Non-null

3.5.2 Checking for missing values

Because they can significantly affect the validity and reliability of analyses and machine learning models, missing values need to be carefully verified. Missing data can introduce bias, reduce statistical power, and lead to inaccurate conclusions. By identifying and addressing missing values early in the data preprocessing stage, analysts can ensure that subsequent analyses are based on complete and reliable data, leading to more accurate insights and model predictions.

```
acidity                       0
indigestion                   0
headache                      0
blurred_and_distorted_vision  0
excessive_hunger              0
muscle_weakness               0
stiff_neck                    0
swelling_joints               0
movement_stiffness            0
depression                    0
irritability                  0
visual_disturbances           0
painful_walking               0
abdominal_pain                0
nausea                        0
vomiting                      0
blood_in_mucus                0
Fatigue                       0
Fever                         0
cramping                      0
type of dosha                 0
prognosis                     0
dtype: int64
```

Fig. 3.3: Missing values

3.5.3 Finding the number of duplicates

Finding the number of duplicates in a dataset is important because they can distort analysis results, leading to biased conclusions and inaccurate model predictions. Removing duplicates ensures that each observation is unique, maintaining the integrity and reliability of the data analysis process.

```
True     546
False    525
dtype: int64
```

Fig. 3.4: Number of duplicates

3.5.4 Removing the duplicates

Removing duplicates from a dataset is essential for ensuring data quality and preventing bias in analysis. Duplicates can skew statistical results and machine learning models by inflating the importance of certain observations. To remove duplicates

3.5.5 Label Encoder

Label encoding is a technique used to transform categorical variables into numerical representations, which is essential for many machine learning algorithms that require numerical input. Here's how label encoding works and its primary use.

3.5.6 Correlation

A statistical tool for describing the relationship between two variables is correlation. It conveys information about their relationship's direction and strength.

1. **Strength of Relationship:**Correlation coefficients vary from -1 to 1. A correlation of one indicates a complete positive link, in which one variable grows proportionately to another. When there is a perfect negative relationship, one variable increases proportionately with the other, as indicated by a correlation of -1. There is no linear relationship between the variables when the correlation value is 0.

2. **Direction of Relationship:** The direction of the relationship is indicated by the correlation coefficient's sign, which can be either + or -. Positive correlation between two variables indicates that the other is more likely to rise as the first does. A negative correlation between two variables means that one is more likely to rise while the other is more likely to fall.

3. **Use in Data Analysis:** Correlation analysis is commonly used in data analysis to understand the relationship between variables. It helps identify patterns, dependencies, and associations in the data. Correlation analysis is particularly useful in feature selection, identifying redundant features, and understanding the impact of variables on each other.

Overall, data exploration, hypothesis testing, and decision-making procedures across a variety of disciplines, including finance, economics, biology, and social sciences, are aided by correlation analysis's insightful understanding of the correlations between variables.

3.5.7 Split the dataset

Separating a dataset into training and testing sets is the most crucial stages in creating a machine learning model. Here is a short summary of the significance of the task and its methodology:

1. **Purpose:**The dataset is divided into segments so that the model's generalisation to previously unseen data can be evaluated. The testing set is used to assess the model's performance after it has been trained using the training set.

2. **Preventing Overfitting:** We can identify overfitting—a situation in which the model becomes adept at memorization of the training set but struggles when faced with fresh data—by assessing the model on a different testing set.

3. **Common Split:** Typically, the dataset is divided into two parts: the testing set, which consists of the final 20–30 of the data, and the training set, which consists of the remaining 70–80 .

4. **Randomness:** In order to guarantee that the training and testing sets are representative of the entire dataset, it is crucial to randomly shuffle the data prior to splitting.

Chapter 4

MACHINE LEARNING ALGORITHMS

4.1 Support Vector Machine

Support Vector Machine (SVM) is defined for regression as well as classification[17].Finding the optimal hyperplane in an N-dimensional space to partition data points into different feature space classes is the main objective of support vector machines (SVMs). The number of features determines the hyperplane's dimension. The hyperplane that shows the greatest margin or separation between the two classes is a plausible candidate for best hyperplane. SVM is robust to **outliers.**

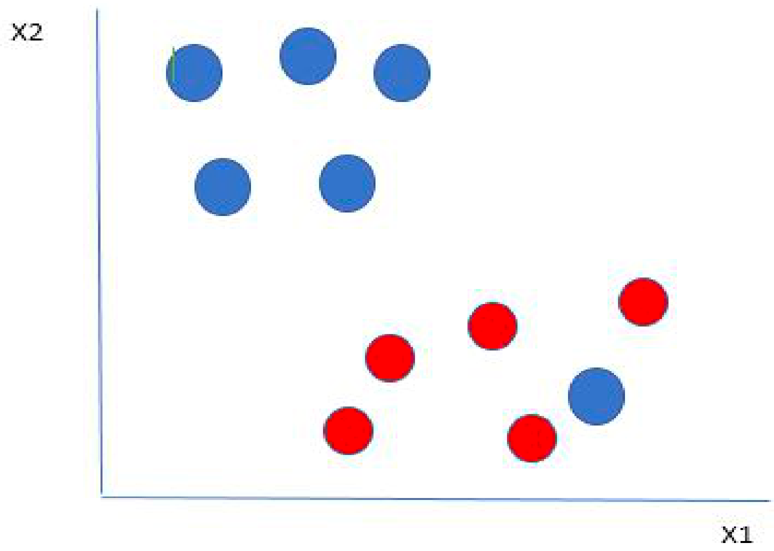

Fig. 4.1: Selecting hyperplane for data with outlier

Two varieties of SVM exist. Both non-linear and linear.When a straight line cannot divide data into two classes (as in the case of 2D), non-linear support vector machines (SVM) can be used to classify the data. We used Non - Linear SVM as there are 4 classes.

4.1.1 Steps for implementation

- Loading the Dataset
- Data Preprocessing
- Building and Training the Model
- Visualization

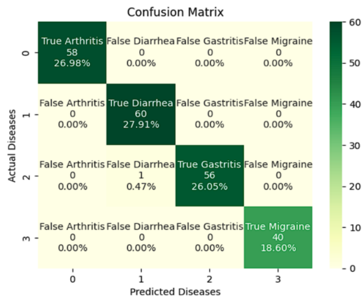

Fig. 4.2: SVM - Full Features

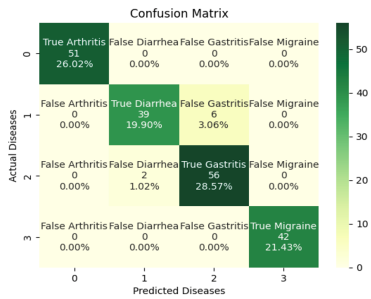

Fig. 4.3: SVM - Selected Features

4.2 Decision Tree Classifier

An example of a tree structure that resembles a flowchart is a decision tree, in which the leaf nodes represent algorithmic results (classes), internal nodes represent features, and branches represent rules. This algorithm for supervised machine learning is adaptable and can be used for both regression and classification problems. The classification rules define the pathways that lead from the roots to the leaves. [18]

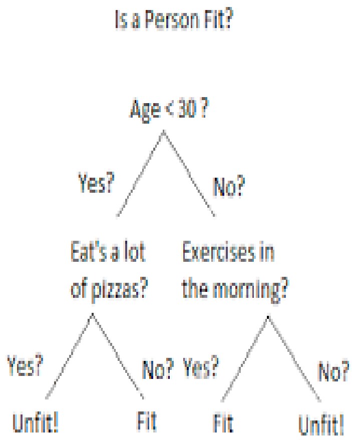

Fig. 4.4: Example of Decision tree

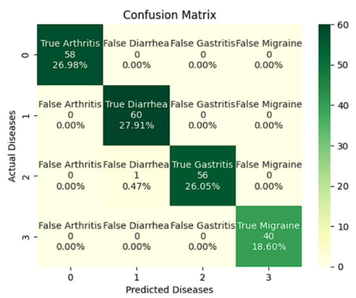

Fig. 4.5: Decision Tree - Full Features

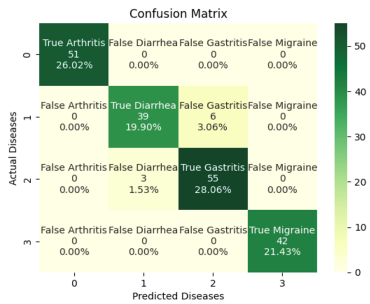

Fig. 4.6: Decision Tree - Selected Features

4.3 K Nearest Neighbors

One supervised machine learning technique that is frequently used for classification is the KNN algorithm (KNN). The field of sickness prediction has made extensive use of it. Using traits and labels from the training set, KNN is a supervised algorithm that forecasts how unlabeled data will be categorised[17][19]. The KNN method can be used to classify datasets whose training dataset model is equivalent to the test study by using the k that are nearest to the test study (i.e., nearest neighbors). It is widely used in categorization assignments due to its highly customisable form and ease of comprehension. Euclidean distance to our metric of similarity Based on the distance measure, it is evident that several data points with the same class label are in close proximity to one another in numerous local locations. K has an impact on the kNN technique. While there are other ways to choose a k-value, one simple way is to run the algorithm iteratively with different k-values and choose the one that works best.

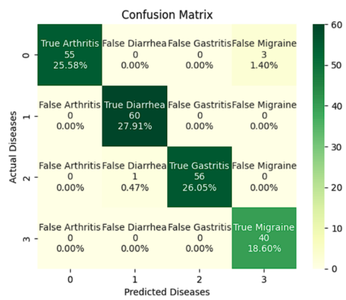

Fig. 4.7: KNN - Full Features

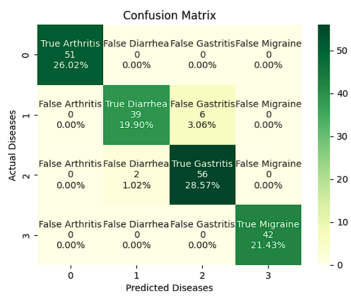

Fig. 4.8: KNN - Selected Features

4.4 XGboost

XGBoost is a distributed gradient boosting library designed for machine learning model training that prioritizes efficiency and scalability. It is an ensemble learning method that combines the predictions of multiple weak models to produce a stronger prediction. The fundamental strategy for boosting is to use weak models in series to construct a model[21]. First, a model is constructed using the training data. The errors in the first model are then attempted to be fixed by building a second model. In this way, models are added until the entire training data set is correctly predicted, or until the maximum number of models is added.[20]

It is a weighted variant of boosted decision trees. To help with outcome prediction, each independent variable is assigned a weight before being fed into the decision tree. The second decision tree receives additional weight and input from the variables that the first decision tree mispredicted. Subsequently, the discrete classifiers and predictors amalgamate to generate a resilient and precise model.

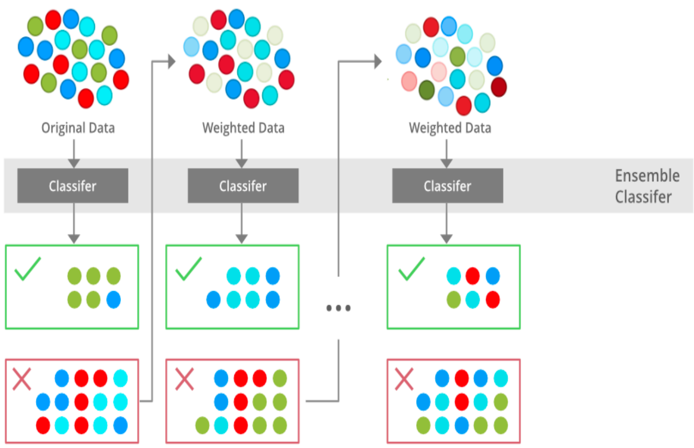

Fig. 4.9: XGboosting

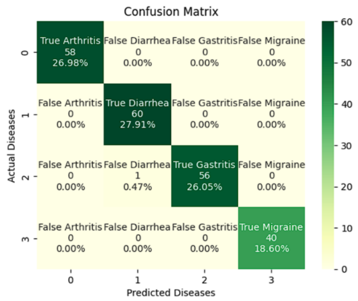

Fig. 4.10: XGboosting - Full Features

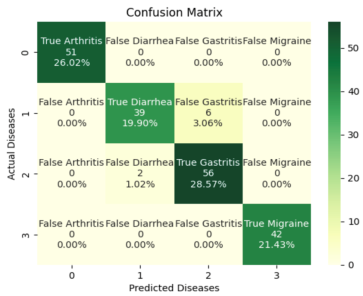

Fig. 4.11: XGboosting - Selected Features

4.5 Logistic Regression

When using the sigmoid function, which accepts input as independent variables and outputs a probability value between 0 and 1, logistic regression is utilised for binary classification. For instance, we have two classes: Class S and Class P. If an input's logistic function value is higher than the 0.5 threshold, it is categorized as being in Class P. Additionally, it's capable of producing probabilistic values between 0 and 1[21].

4.5.1 Types

- The variable in a statistical model called binomial logistic regression can have just two potential values, such as 0 or 1.
- Multinomial: Multinomial When the variable that is dependent has three or more alternative unordered categories, such as "hen," "fish," or "crabs," logistic regression is employed.
- The dependent variable in an ordinal logistic regression may contain three or more ordered categories, such as "low," "medium," or "high."[22]

The result of the sequential regression model in continuous values is transformed into a categorical value output by the logistic regression model using a sigmoid function. With the help of this sigmoid function, any set of real-valued independent variables can be converted to a value between 0 and 1.

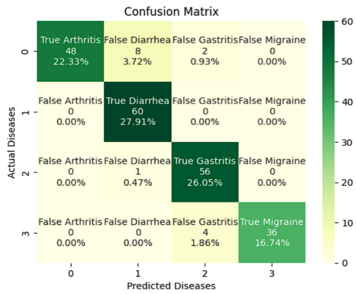

Fig. 4.12: Logistic Regression - Full Features

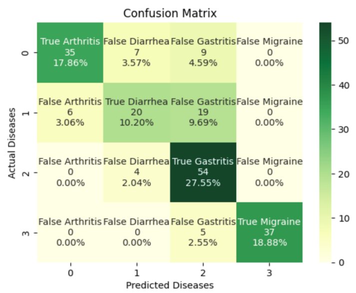

Fig. 4.13: Logistic Regression - Selected Features

4.6 Evaluation

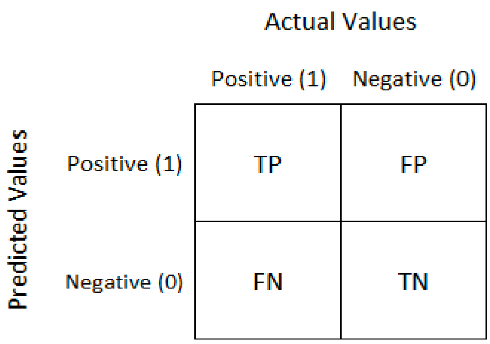

Fig. 4.14: Contingency table

- Accuracy:The percentage of correctly classified instances is provided by accuracy.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4.1}$$

- Precision refers to the degree of precision in optimistic forecasts.

$$Precision = \frac{TP}{TP + FP} \tag{4.2}$$

- The percentage of accurately predicted actual good cases in all instances is known as recall.

$$Recall = \frac{TP}{TP + FN} \tag{4.3}$$

- The harmonic mean of recall and precision tends to produce the F1 score.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.4}$$

4.7 Machine Learning Results with All Features

Machine Learning Algorithms	**Accuracy(A)**	**Precision(P)**	**Recall(R)**	**F1 score**
Decision Tree	99.5%	100%	100%	100%
XG Boost	99.7%	100%	100%	100%
Supported Vector Machine	96%	96%	96%	96%
Logistic Regression	94%	94%	93%	93%
KNN	99.4%	99.5%	99.5%	99%

Table 4.1: ML Characteristics with Full Dataset Features

Chapter 5

FEATURE EXTRACTION METHODS

5.1 Principal Component Analysis(PCA)

A statistical method called principal component analysis (PCA) is used to minimize a dataset's dimensionality while preserving the possible amount of information[23]. The principal components of the newly created variables are linear combinations of the original variables, and they are created by identifying the most significant features or variables within the dataset.

In unsupervised learning, Principal Component Analysis (PCA) is a method used to examine the connections among a set of variables.A statistical method called Principal Component Analysis (PCA) uses an orthogonal transformation to convert a set of correlated variables into a set of uncorrelated variables.Without any prior knowledge of the target variables, the main goal of Principal Component Analysis (PCA) is to reduce the number of dimensions in a dataset while maintaining the most important patterns or connections between the variables.The way Principal Component Analysis (PCA) works is by calculating each characteristic's variance. This is due to the fact that characteristics with high variance typically show a distinct difference between classes, which makes dimensionality reduction easier.[23].

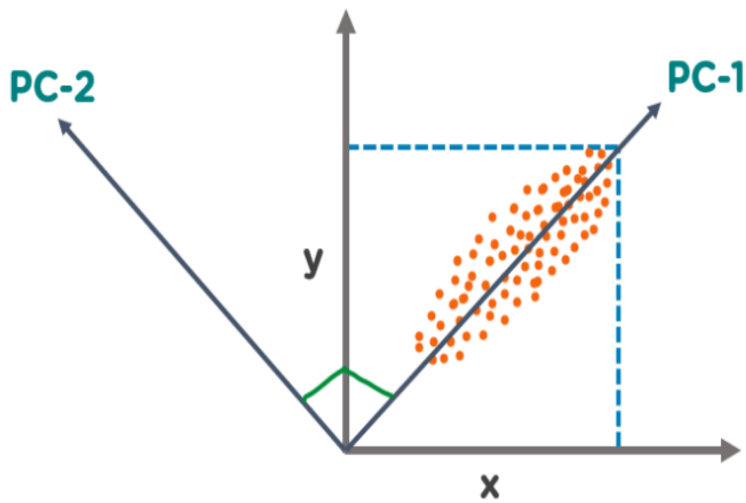

Fig. 5.1: Principal Component Analysis

Correlation indicates the degree of association between two variables. For example, if one variable is altered, the other variable is also modified. The correlation coefficient varies between -1 and +1. In this context, the value of -1 implies that the variables are inversely proportional to each other, whereas a value of +1 shows that the variables are directly proportional to each other. Orthogonal: This term indicates that variables are independent of one other, resulting in a correlation coefficient of 0 between the pair of variables. Eigenvectors are non-zero vectors that produce a scalar multiple of themselves when multiplied by a square matrix M. A vector that meets the formula Av = λv, where A is a matrix and λ is a scalar, is called an eigenvector (v). The Covariance Matrix is a matrix that contains the covariance between pairs of variables.

```
Eigen Vectors [[-0.15187608  0.00568291 -0.28836487 ... -0.06666207 -0.03449515
   0.084765  ]
 [-0.14059612  0.09876244 -0.18077253 ...  0.0189302  -0.05174382
   0.05350464]
 [ 0.00042377 -0.23186635 -0.04717263 ...  0.01518063  0.08315044
  -0.08717657]
 ...
 [ 0.01195895  0.12480709 -0.37536935 ...  0.22635589 -0.19111575
   0.15539708]
 [ 0.04458999  0.2588741   0.27110395 ...  0.3403702  -0.48615028
  -0.06530783]
 [ 0.273813    0.16709567  0.02946374 ... -0.02206664 -0.02251139
   0.04299271]]
Eigen Values [8.96487405 4.67186007 2.61567326 2.30080742 1.08679061 0.96591134
 0.07024758 0.7892631  0.12308854 0.7447668  0.70501326 0.68145918
 0.62862386 0.21557559 0.59478388 0.24433118 0.25342952 0.56713884
 0.54096771 0.53561004 0.51305098 0.29581647 0.47273445 0.44346492
 0.43709697 0.42482374 0.32457974 0.33822206 0.3889519  0.35463628
 0.37317743 0.36313578]
```

Fig. 5.2: Eigen Vectors and Eigen Values

```
Eigenvalues with Feature Names:
acidity: 8.964874049649792
indigestion: 4.671860070244034
headache: 2.6156732553501367
blurred_and_distorted_vision: 2.3008074240458
excessive_hunger: 1.0867906051993392
muscle_weakness: 0.9659113382333551
swelling_joints: 0.7892631001124495
depression: 0.74476680010099
irritability: 0.7050132594415344
visual_disturbances: 0.6814591816983974
painful_walking: 0.628623862385123
nausea: 0.594783884023366
Fatigue: 0.5671388440550454
Fever: 0.5409677057340112
Dehydration: 0.5356100370303495
loss_of_appetite: 0.5130509811980326
blood_in_stool: 0.4727344511232899
gnawing: 0.443464917352529
upper_abdomain_pain: 0.4370969704965705
fullness_feeling: 0.4248237378897975
heartburn: 0.38895190027332843
burning_ache: 0.3731774264897661
type of dosha: 0.3631357846652717
belching: 0.35463628241970674
abdominal_bloating: 0.3382220588114275
hiccups: 0.3245797354875175
cramping: 0.29581646632561015
blood_in_mucus: 0.25342951826803084
vomiting: 0.2443311781987832
abdominal_pain: 0.215575591570787
movement_stiffness: 0.12308854153597369
stiff_neck: 0.07024758264594666
```

Fig. 5.3: Eigen Values with features

5.2 Major features for particular disease

```
Disease Classification: Migraine
Eigenvalues with Feature Names:
acidity: 1.7051099876856755
indigestion: 1.4147489881651332
excessive_hunger: 1.2862876417199418
muscle_weakness: 1.2176137627168986
stiff_neck: 1.183309691433393
swelling_joints: 1.0339168058317265
movement_stiffness: 0.9413497627044188
depression: 0.8777427372642257
irritability: 0.8204718487711866
painful_walking: 0.7434280782637187
visual_disturbances: 0.7298775223731016
blurred_and_distorted_vision: 0.5816886975143226
headache: 0.5148420724554859
```

Fig. 5.4: Migraine - Eigen Vectors and Eigen Values

```
Disease Classification: Arthritis
Eigenvalues with Feature Names:
acidity: 1.5192024960633712
indigestion: 1.4881579938250697
headache: 1.3347632047729583
blurred_and_distorted_vision: 1.1587712315970358
painful_walking: 1.063660778765785
visual_disturbances: 1.0328320453153055
irritability: 0.9788245002816933
depression: 0.8502525634595641
movement_stiffness: 0.8353522982027515
swelling_joints: 0.79668486435446
stiff_neck: 0.7207605549760562
muscle_weakness: 0.654027959511897
excessive hunger: 0.6170971057732865
```

Fig. 5.5: Arthritis - Eigen Values with features

```
Disease Classification: Diarrhea
Eigenvalues with Feature Names:
acidity: 2.484475104343585
indigestion: 1.5447468357721619
headache: 1.3181020318477552
excessive_hunger: 1.1411218939305978
movement_stiffness: 0.9066564950508967
irritability: 0.852258719572392
depression: 0.822595437796122
swelling_joints: 0.6906912626147953
stiff_neck: 0.5427790252415509
muscle_weakness: 0.4527061853367394
blurred_and_distorted_vision: 0.28329353179090316
```

Fig. 5.6: Diarrhea - Eigen Values with features

```
Disease Classification: Gastritis
Eigenvalues with Feature Names:
acidity: 4.310173763957892
indigestion: 2.0967204572731872
headache: 1.2169609700655846
blurred_and_distorted_vision: 1.0892933016208766
excessive_hunger: 0.8146103626271541
stiff_neck: 0.6998834279367435
swelling_joints: 0.6694554906425111
visual_disturbances: 0.5763103191528527
abdominal_pain: 0.5285124164822119
painful_walking: 0.5090198692281234
irritability: 0.43856141247831937
depression: 0.40449445363252434
movement_stiffness: 0.3973068367730637
muscle_weakness: 0.3001675063642552
```

Fig. 5.7: Gastritis - Eigen Values with features

5.3 Machine Learning Results with Selected Features

Machine Learning Algorithms	Accuracy	Precision	Recall	F1 score
Decision Tree	95%	96%	96%	96%
XG Boost	96%	96%	96%	96%
Supported Vector Machine	96%	96%	96%	96%
Logistic Regression	74%	78%	74%	74%
KNN	94%	95%	94%	94%

Table 5.1: ML Characteristics with Selected Features

Chapter 6

EXPERIMENT BY HARDWARE

6.1 Photoplethysmography Heart Rate Sensor

In order, to measure the heart rate in beats per minute in advanced level we use the 'PPG based Heart Rate Sensor'. The 'PPG Heart Rate Sensor' is a simple and inexpensive optical technology for detecting blood volume changes under the tissues. Analog pulse mode and digital square wave mode are the two signal output modes used by the heart rate sensor. [16]

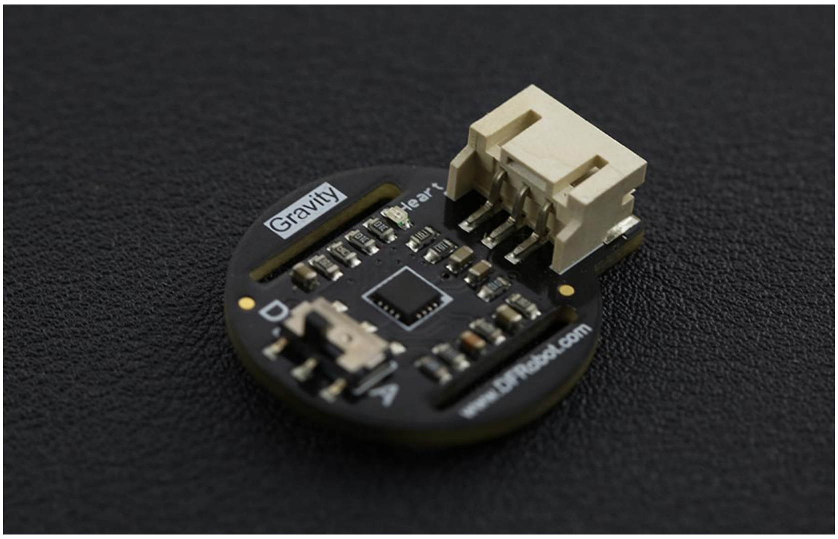

Fig. 6.1: PPG Heart Rate Sensor

6.2 Hardware Block Diagram

Fig. 6.2: Block Diagram - Hardware

6.3 Experimental Hardware Setup and Measurement

In the setup experiment, first we have to connect the 'Heart Rate Sensor', to the Arduino UNO board, as per the given figure 6.3 and the given table 6.1.

.

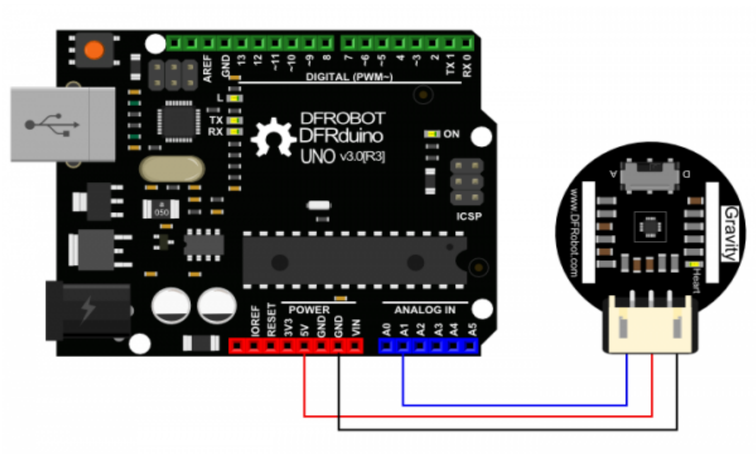

Fig. 6.3: Connection of Heart Rate Sensor and Arduino UNO

Heart Rate Sensor	**Arduino UNO**
Ground	Ground
VCC	5V
Signal	A1 (Analog Pin)

Table 6.1: Sensor Connections

Now, using the Arduino IDE software, we coded in-order to measure the beats per minute (bpm) from each persons. Using, the sensor and Ardino UNO, we calculate the beats per minute (bpm) for each person. By, using the sensor we calculate 3 dosha values from two hands, so it's totally 6 values per person. And, later we convert output data in an excel sheet format as a dataset.

6.4 Experimental Results

Name	Vaatha	Pittha	Kapha
Sample 1	98 - 100	92 - 101	88 - 98
Sample 2	75 - 81	71 - 78	73 - 81
Sample 3	81 - 90	81 - 88	87 - 93
Sample 4	83 - 92	82 - 88	75 - 89
Sample 5	63 - 74	66 - 71	69 - 74

Table 6.2: Ayurvedic Analysis

Note: The heart rate values calculated have to be consulted with ayurvedic experts.

Later, we have to calculate the average bpm for each sample as shown in output figure6.4.

```
Data has been filtered and stored in output_data.csv
First 60 filtered samples:
100
100
99
98
98
99
100
100
100
99
92
92
90
92
92
90
89
89
89
89
90
89
89
89
89
90
91
91
91
93
```

```
94
94
94
92
94
92
92
92
91
91
91
93
95
98
96
100
100
96
89
91
93
92
93
94
94
94
94
94
94
94
Average of first 60 filtered samples: 93.5
```

Fig. 6.4: Average calculation for a sample

Later, we have to classify the average value according to the dosha normal and abnormality range table as shown in the figure 6.5.

Dosha	Normal Range	Abnormal Range
Vaata	80 – 90 bpm	Less than 80 bpm Or More than 90 bpm
Pittha	70 – 80 bpm	Less than 70 bpm Or More than 80 bpm
Kapha	60 – 70 bpm	Less than 60 bpm Or More than 70 bpm

Fig. 6.5: Normal and Abnormal range for Dosha

As, the calculated value is 93.5 bpm for that sample, it comes under the abnormal range of Vaata dosha, with a higher heart rate. Now according to the heart rate abnormality table, we can identify the symptoms of the sample from the below table figure6.6, by evaluating the sample along with the help of the expert too.

Dosha	High Heart Rate	Low Heart Rate
Vaata	Headache, Abdominal Indigestion, Acidity, High B.P., Asthma, Breathing Suffocation, Heart Palpitations (stress, anxiety), Common Cold, Lung Problems, Body trembling, Shoulder Pain, Arthritis, Toothache, stroke	Low B.P., Heart Palpitations (medication side effects, electrolyte imbalance), Loose motion, Throat infection
Pithha	Headache, Allergy, Eyesight problems, Breathing Suffocation, Digestion Problem, Eye Cataract, High Weight, Joint Pain, Abdominal Indigestion, Gastritis, Diarrhea, Mental health, short temper, sleeping problem's, weight loss	Loose motion, Low masculinity, Low RBC, Low Iron Content, Dizziness, Dry Lips
Kapha	Headache, Shoulder pain, Body trembling, Heart Palpitation (stress, anxiety), Neck Stiffness, Hand trembling, Breathing Problems (Tachycardia), Throat Pain, common cold	Heart Palpitations (medication side effects, electrolyte imbalance), Breathing Problem (Bradycardia), lungs problems

Fig. 6.6: List of symptoms during abnormal heartrate

So, from the above table figure 6.6 we can say, the sample patient may have a chance of headache, indigestion, etc. By, the Machine Learning model designed, we can classify what type disease, is this?, we can verify with it.

Chapter 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

In the context of Ayurveda, the report addresses the use of machine learning classifiers for disease diagnosis utilizing wrist pulse signals. In order to detect health concerns early on, it emphasizes the significance of tailored diagnosis, the flexibility of machine learning models, and the capacity to discern between normal and pathological signal patterns.

In order to improve diagnostic speed and accuracy, the research also highlights the importance of fusing modern technologies with ancient Ayurvedic diagnostic procedures. The study demonstrates how the XG Boost method outperforms other machine learning models, such as Decision Tree, SVM, and Logistic Regression, in terms of accuracy, reaching 96%.

To sum up, the findings in the article show how machine learning algorithms can be used to use wrist pulse data to diagnose diseases, opening new avenues in this area.

7.2 Future Scope

1. The precision of disease diagnosis from wrist pulse signals can be increased with the development of more advanced machine learning algorithms, such as deep learning and reinforcement learning.

2. Integration with wearable technology makes it possible to analyse wrist pulse data in real time and monitor patients continuously, giving dynamic insights into their health.

3. Extracting relevant aspects from raw pulse data, such as heart rate variability, waveform morphology, and temporal patterns, using advanced signal processing techniques.

4. Using advanced sensors, an instumental device can be developed to calculate the vaatha, pittha, and kapha simultaneously to identify the symptoms, by checking up each the heart rate.

5. It is essential to increase the precision of signal processing techniques in order to more effectively remove noise from wrist pulse signals and extract pertinent characteristics.

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