A Minor Project Report
On

HUMAN RECOGNITION USING GAIT ANALYSIS

SUBMITTED IN PARTIAL FULFILLMENT FOR THE AWARD OF DEGREE OF

Bachelor of Technology

IN

Electronics and Communication Engineering

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DECEMBER, 2019

CERTIFICATE

This is to certify that the minor project report entitled, "**Human Recognition Through Gait Analysis**" submitted by **Apoorv Khare, Vivek Garg** and **Naman Wadhwa** in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in **Electronics and Communication Engineering** of the Jaypee Institute of Information Technology, Noida is an authentic work carried out by them under my supervision and guidance. The matter embodied in this report is original and has not been submitted for the award of any other degree.

Signature of Supervisor:

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DECLARATION

We hereby declare that this written submission represents our own ideas in our own words and where others ideas or words have been included have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission.

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ABSTRACT

Human motion analysis has been an active research area over the last decade, with applications in surveillance and analysis of clinical and sports videos. Although traditional approaches are based on markers or feature points, we are interested in marker less methods. We focus on a specific category of human motion, i.e., walking. In this project, we build our work by researching on modelling periodic signatures that are generated by human motion.

In this project we focus on a new feature extraction technique known as GEI i.e. Gait Energy Image. This is one of the most effective and efficient energy image extraction technique for marker less or model free techniques.

We then apply classifier machine learning algorithms which helps us to identify the model which is best for Human Recognition. The comparative analysis gives us an insight as what model must be preferred which is then verified by the ROC curves in the later half.

Recognizing people by their gait has become more and more popular nowadays due to the following reasons. First, gait recognition can work well remotely and is non-invasive. Second, gait recognition can be done from low-resolution videos and with simple instrumentation. Third, gait recognition can be done without the cooperation of individuals. Fourth, gait recognition can work well while other features such as faces and fingerprints are hidden. Finally, gait features are typically difficult to be impersonated.

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CHAPTER 1
INTRODUCTION

People often feel that they can identify a familiar person from afar simply by recognizing the way the person walks. This common experience, combined with recent interest biometrics, has led to the development of gait recognition as a form of biometric identification. As a biometric, gait has several attractive properties. Acquisition of images portraying an individual's gait can be done easily in public areas, with simple instrumentation, and does not require the cooperation or even awareness of the individual under observation. In fact, it seems that it is the possibility that a subject may not be aware of the surveillance and identification that raises public concerns about gait biometrics. There are also several confounding properties of gait as a biometric. Unlike finger prints, we do not know the extent to which an individual's gait is unique. Furthermore, there are several factors, other than the individual, that cause variations in gait, including footwear, terrain, fatigue, and injury

In 1994, the earliest gait recognition system was proposed by authors in reference, which was based on a small gait database. Then, the Defence Advanced Research Projects Agency (DARPA) developed the famous HumanID program, which set up the first publicly accessible database or gait recognition. Since then, researchers have done many works on gait recognition. Early gait recognition systems are mainly based on video. There are two sorts of video-based approaches, namely model-free and model-based approaches, as illustrated below. Model-based approaches model human body and extract features from the model.

In 1997, the pendulum was used for modelling leg movement. And the transformation of legs inclination in the video was used for gait recognition. In 2002, the cadence and stride were used for gait recognition. In 2003 the human body was used as 2D figures, and computed trajectory-based kinematic features in the video for gait recognition. In 2004, the 3D temporal models were introduced. In contrast, model-free approaches did not model gait previously, and they represent the human gait as a whole without knowing the underlying structure of the human body. In 2007,the model-free gait representation method named Gait History Image (GHI) was introduced. Recently, gait recognition has been done through sensor readings such as accelerometer, floor sensors, and radars.

Early medical and psychological studies showed that human gait had 24 different components, which could be used for identifying an individual. Moreover, in the previous works, it was shown that the light points attached to individuals' joints could be used for representing a human motion, and point light displays could be used for distinguishing human activities. All the above works indicated that every individual had unique muscular-skeletal structure, which could be used for identifying him/her. Therefore, gait recognition is feasible. Traditionally, gait-based authentication has been studied through analysing the videos of human motion. However, the ubiquity of smart phones equipped with accelerometers and gyroscopes has opened a new dimension to gait-based authentication because of the unique ability to capture gait patterns by accelerometer and gyroscope. In addition, wide spread applications and advances in machine learning have resulted in improved accuracies.

This project aims to establish a model-free gait representation method named Gait Energy Image (GEI), which represents features in the video as a single image and apply machine learning classifier algorithms for human recognition.

1.1. Motivation

Since gait recognition has so many unique properties, it has attracted much attention in the past 20 years.

The applications of gait recognition are immense, which became a major factor in our motivation for Human Recognition.

1. **Medical diagnostics:**
    a. Pathological gait - reflect compensations for underlying pathologies, or be responsible for causation of symptoms in itself.
    b. Chiropractic and osteopathic utilization - Observation of gait is also beneficial for diagnoses in chiropractic and osteopathic professions as hindrances in gait may be indicative of a misaligned pelvis or sacrum
    c. Comparative biomechanics - By studying the gait of non-human animals, more insight can be gained about the mechanics of locomotion, which has diverse implications for understanding the biology of the species in question as well as locomotion more broadly.

2. **Sports Analysis:** Sport scientists use gait analysis to translate muscular contractions about articulating joints into functional accomplishment. Athletes and their coaches use gait analysis techniques in ceaseless quest for meaningful improvements performance avoiding any injuries
3. **Biometrics:** Gait has been established as biometrics to recognize people by the way they walk. This advances in gait recognition has therefore led to the development of techniques for forensics use since each person can have a gait defined by unique measurements such as the locations of ankle, knee, and hip.

1.2 OUR APPROACH

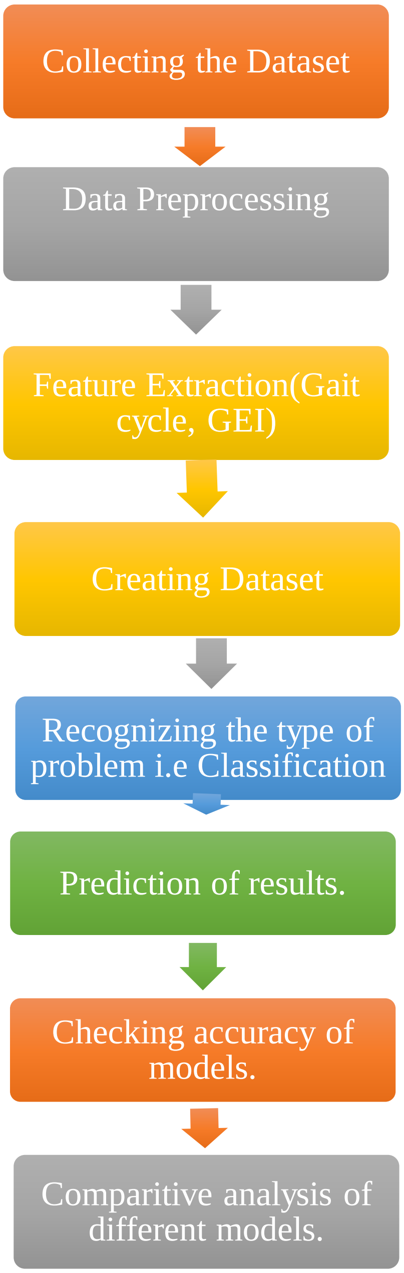


Fig 1.1 Flow chart of process

Chapter 2
Literature Survey

A lot of research papers have been referred for this project. Our main purpose is to find a working of a non-invasive biometric which is able to identify an individual who is far away from the physical sensor. The main purpose of it is that as many non-cooperating individuals whom we wish to identify can be identified. It should be taken care as this technology should be in the right hands of people. Many algorithms have been proposed, comparison of different algorithms and evaluation of robustness to some variations such as the variations of view angle, clothing, shoe types, surface types, carrying condition, illumination, and time are still hard and open problems, as discussed by Tan et al. [1]. For these problems mentioned above, we are choosing a data set with a variety of applicative uses as for the development and statistically reliable evaluation of gait-recognition approaches, the construction of a common gait database is essential, as mentioned by Iwama et al. [2].

From a surveillance perspective, gait recognition is an attractive modality. This is because it is capable of identifying humans at a distance by inspecting their walking manners. It can also be performed surreptitiously in an unconstrained environment, acclaimed by Kusakunniran et al. [3]. Gait is one of the few biometric features that can be measured remotely without any sort of physical contact and proximal sensing, which make it useful in surveillance applications. These applications play a very important role in monitoring high security areas such as airports, banks, military zones and railway stations which are in a high terror activity probability zone. The approaches for gait analysis can be mainly divided into two categories: model-based methods and appearance-based methods by Zhang E et al. [4]. As our dataset is taken from OU-ISIR which is in the form of combination of silhouettes, GEI feature extraction is the best process to extract for a model free approach. While extracting GEI we need the features to be same in every GEI output. Thus, we need to provide a specific periodic sequence of silhouettes to GEI. Considering individual recognition by activity specific human motion i.e. regular human walking, which is used in most current approaches of individual recognition by gait given by Han.et.al[5]

Chapter 3

Gait Analysis

3.1 Introduction to Gait

Gait means a person’s manner of walking. Human Gait is defined as a translatory progression of the body as a whole produce by coordinated, rotatory movements of body segments.

Gait has two phases: swing phase and stance phase. Swing phase occurs when the foot is not in contact with the ground, beginning when the foot leaves the ground and ending with the heel strike of the same foot. The stance phase is comprised of all the activity that occurs when the foot is in contact with the ground, beginning with heel strike and ending with toe off of the same foot. The stance phase accounts for 60% of the gait cycle, leaving 40% of the gait cycle to the swing phase.

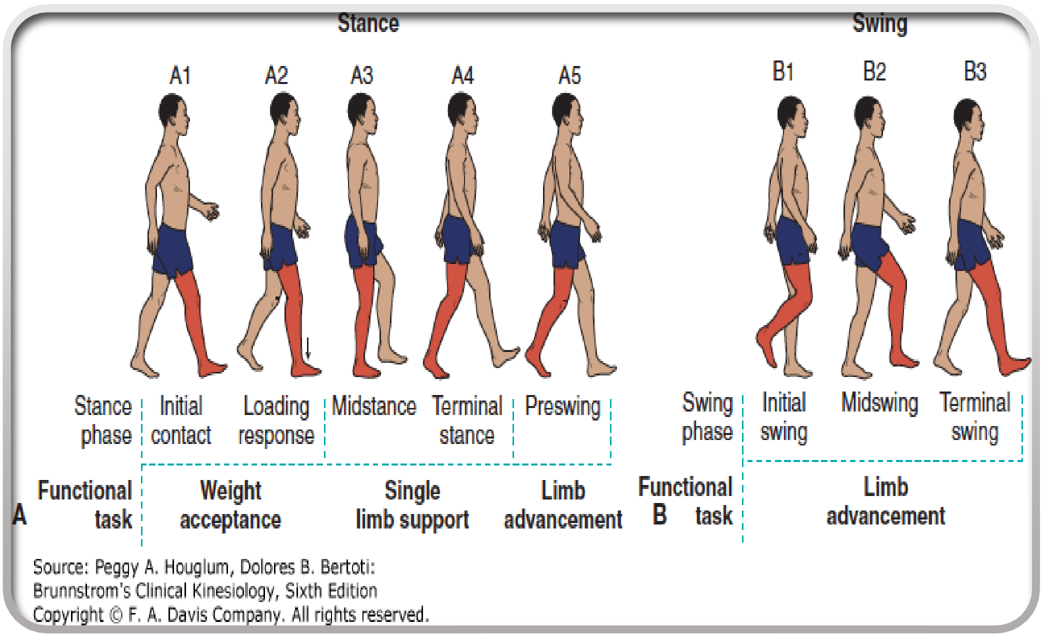


Figure 3.1 Illustration of Gait

3.2 Types of Gait analysis

There are two types of Gait Analysis methods: -

1. **Model Based method**
2. **Model Free method**

3.2.1 Model Based Approach

Model-based approaches are based on prior knowledge and often require both a structural and a motion model to capture both static and dynamic information of the gait. The model can be a 2- or 3-dimensional structural (or shape) model and motion model that lays the foundation for the extraction and tracking of a moving person. An alternative to a model-based approach is to analyse the motion of the human silhouette deriving recognition from the body's shape and motion.

The main advantages of the model-based approach are that it can reliably handle noise, scale and rotation well, as opposed to silhouette-based approaches.

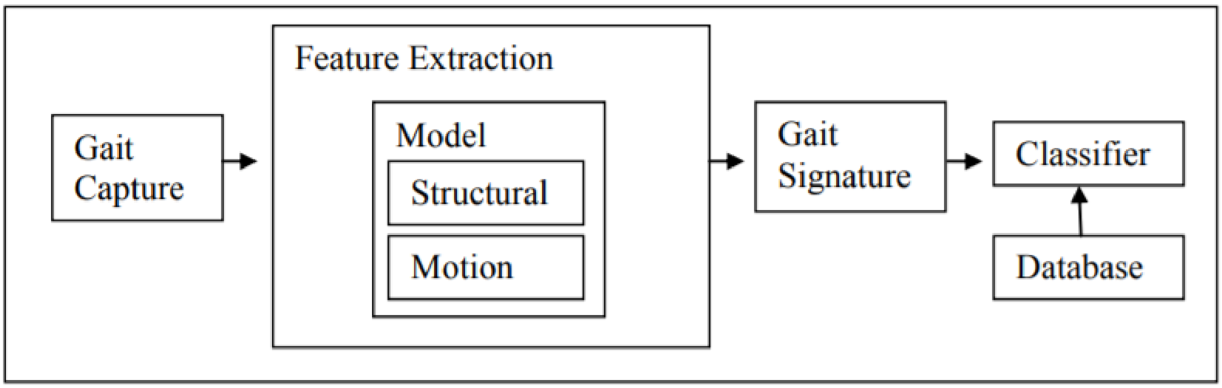


Figure 3.2 Components of model-based recognition system

A structural model is a model that describes the topology or the shape of human body parts such as head, torso, hip, thigh, knee and ankle by measurements such as the length, width and position. This model can be made up of primitive shapes (cylinders, cones, and blobs), stick figures, or arbitrary shapes describing the edge of these body parts. On the other hand, a motion model describes the kinematics or the dynamics of the motion of each body part. Kinematics generally describe how the subject changes position with time without considering the effect of masses and forces, whereas dynamics will take into account the forces that act upon these body masses and hence the resulted motion. When developing a motion model, the constraints of gait such as the dependency of neighbouring joints and the limit of motion in terms of range and direction has to be understood.

3.2.2 Model Free Approach

In this approach we observe the motion of the human and extract different type of features from that motion.

This approach is being used in this project.

Model-free features are categorized as temporal and spatial**. In model free approaches, some techniques are frame based and some techniques are gait cycle based. The project work is done on gait cycle-based approach.**

However, they can be further organized in four sub-categories:

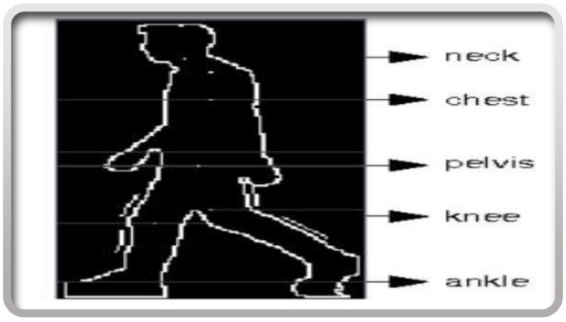
- Contours
- Silhouettes
- Energy
- Depth

Contours: they have low computational cost but suffer from intraclass variations.

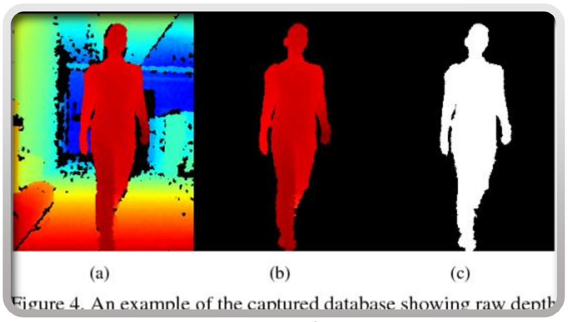
Silhouettes: a whole silhouette is taken into consideration per subject. This can be advantageous because the errors of silhouette segmentation are avoided

Energy: energy features attempt to extract the spatial and temporal information of the gait using a single and robust signature. The average image representation along a gait cycle is a good example

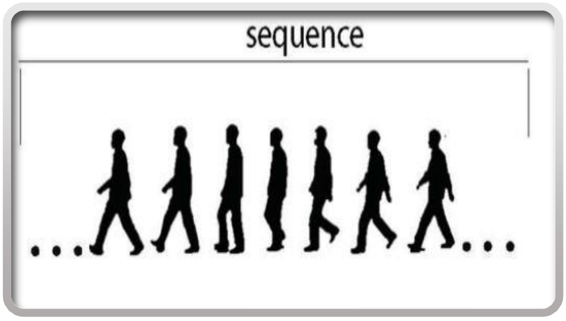
Depth: instead of using solely colour images, some works tried to exploit depth information based on devices such as Microsoft Kinect.



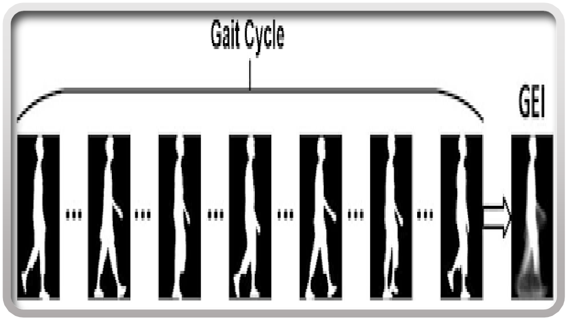
Contours



Depth



Silhouettes



Energy

Figure 3.3 Illustration of model free features

Chapter 4

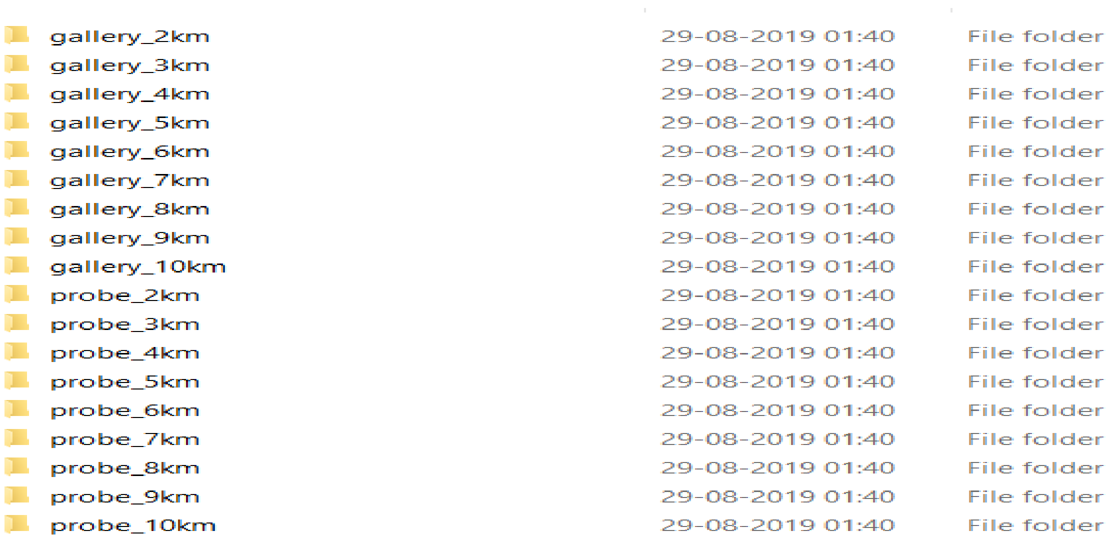
Dataset Pre-processing

4.1 Introduction to Dataset

Dataset is important in Evaluating the accuracy of the gait recognition system.

The dataset we are using is **OU-ISIR Gait Treadmill (A)Dataset** (Osaka University- Institute of Scientific and Industrial Research). Treadmill dataset contains gait images of subjects on a treadmill with the largest range of view variations: 25 views, 9 Speed variations between 2 and 10 km/h). And dataset is distributed in a form of silhouette sequences registered and size-normalized to 88 by 128 pixels size

This dataset is divided into Gallery and Probe where Gallery stands for Training and Probe



gallery_2km	29-08-2019 01:40	File folder
gallery_3km	29-08-2019 01:40	File folder
gallery_4km	29-08-2019 01:40	File folder
gallery_5km	29-08-2019 01:40	File folder
gallery_6km	29-08-2019 01:40	File folder
gallery_7km	29-08-2019 01:40	File folder
gallery_8km	29-08-2019 01:40	File folder
gallery_9km	29-08-2019 01:40	File folder
gallery_10km	29-08-2019 01:40	File folder
probe_2km	29-08-2019 01:40	File folder
probe_3km	29-08-2019 01:40	File folder
probe_4km	29-08-2019 01:40	File folder
probe_5km	29-08-2019 01:40	File folder
probe_6km	29-08-2019 01:40	File folder
probe_7km	29-08-2019 01:40	File folder
probe_8km	29-08-2019 01:40	File folder
probe_9km	29-08-2019 01:40	File folder
probe_10km	29-08-2019 01:40	File folder

stands for Testing.

Figure 4.1 Showing dataset storage

4.2 Pre-processing

It consists of detection of subject, extraction of the silhouette and extraction of the feature. Once the walking subject is captured from a distance, then background subtraction is performed on the image by using background subtraction techniques like Running Gaussian Average, Temporal Median Filter, etc. (BINARISTION OF DATA)

Here, the video is captured from a camera of a subject which is converted into frames for pre-processing. After obtaining frames detection of subject happens and background elimination takes place and these newly obtained images are normalized, height of subject is adjusted and finally it is reduced to a size of 88*128 pixels. Hence, we obtain a sequence of silhouette.

Figure 4.2 Sequence of silhouette of particular subject belonging to gallery_2km

4.2.1 Gait Cycle

Gait Cycle is the time period or sequence of movements during locomotion in which one-foot contacts the ground to when that same foot again contacts the ground. A single gait cycle is also known as a stride.

We in this project are using period based, energy model free technique

In order to calculate the gait cycle in our dataset, we follow these steps:

1. We calculate the white pixels of the silhouettes representing the concerned subject
2. The result obtained from the above step is converted to a graph.
3. In order to locate the same foot which contacts the ground to when that same foot again strikes the ground
4. We extract the maxima of the graph and calculate the gait cycle by taking the difference of x-coordinate of alternate maximas.

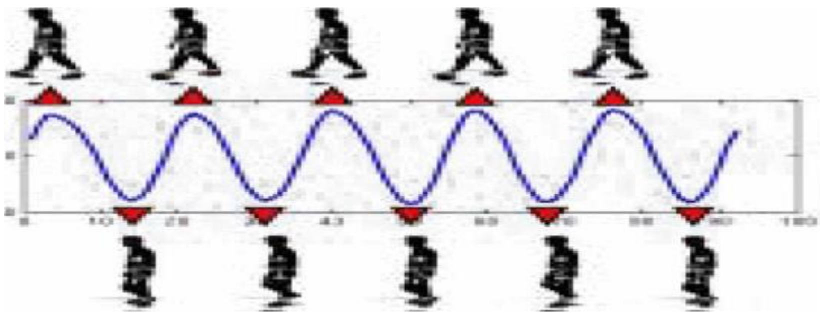


Figure 4.3 An illustration of calculation of the gait cycle.

Advantages of the Gait cycle:

The gait cycle analysis performs two important functions.

1. First, it determines the frequency and phase of each observed conduction sequence, allowing us to demonstrate the dynamic time to align the sequences before matching.
2. Secondly, it provides data reduction by summarizing the sequence with a small number of prototype key frames.

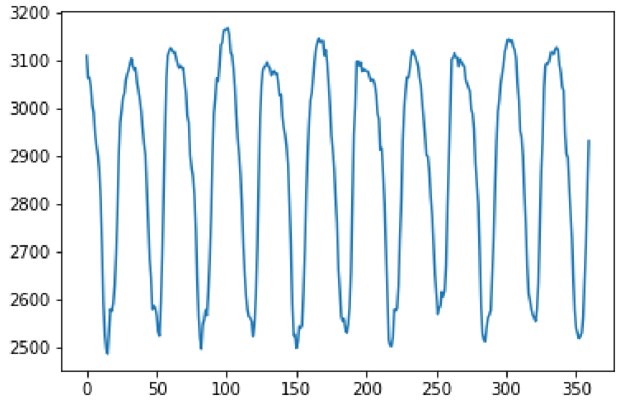


Figure 4.4 Showing the Actual Graph of White Pixels

After all this processing, Using model free approach we perform features extraction using GEI(Gait Energy Image) method and saving them in CSV file mode.

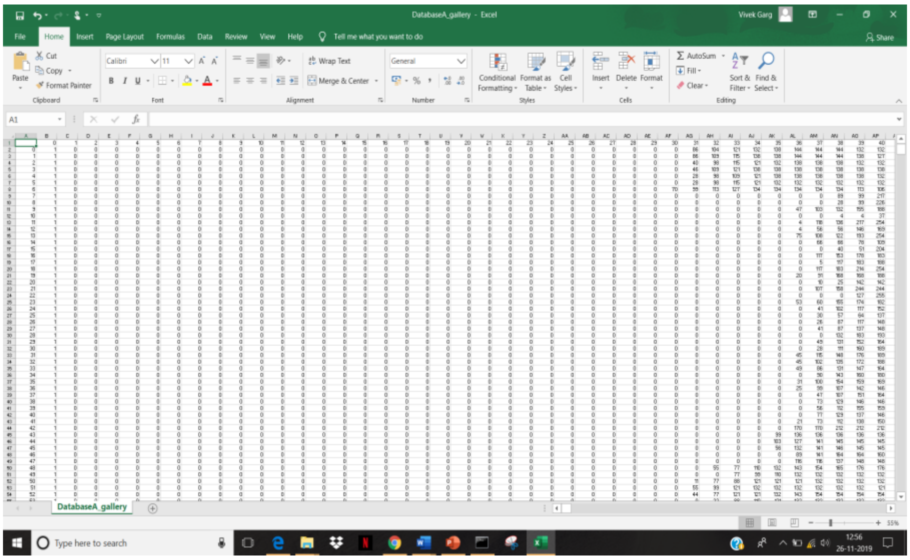


Figure 4.5 Training Database after feature extraction

CHAPTER 5
FEATURE EXTRACTION

5.1. Gait Energy Image (GEI) Representation [ ]

5.1.1 INTRODUCTION

Gait energy image (GEI) preserves the dynamic and static information of a sequence obtained by using **Gate Cycle.**. The common static information includes the appearance and shape of the human body and the dynamic information includes the variation of frequency and phase.

5.1.2 Representation Construction

We believe that the silhouettes are derived from original human meandering scenes. A silhouette pre-processing process is then applied to the extracted silhouette sequences. This includes shape normalization (proportionally resizing each silhouette image so that all silhouettes have the same height) and horizontal alignment (the upper half silhouette portion is centered with respect to its horizontal centroid). In a pre-processed silhouette sequence, the lower half silhouette-shaped time series signal from each frame indicates the move frequency and phase information. We estimate the gait frequency and phase by estimating the maximum entropy spectrum from the time series signal. Given the pre-processed binary Gait silhouette images B (x, y) at time t in a sequence, the gray-level Gait energy image (GEI) is defined as follows:

$$G(x,y) = \frac{1}{N}\sum_{t=1}^{N} B_t(x,y),$$

Where N is the number of frames in the complete cycle (S) of a silhouette sequence, T is the frame number in the sequence (moment of time), and x and y are the values in the 2D image coordinate. As expected, GEI shows the major shapes of silhouettes and their changes on the gait cycle.

We refer to this as the gait energy image because:

1) Each silhouette image is a space-normalized energy image that moves over it,

2) GEI is the time-normalized accumulated energy image of the human cycle in a full cycle.

3) Pixel with high intensity value in GEI means that in this case the human is moving more (i.e., with higher energy). GEI targets specific general human walking and we use GEI as a gait template for personal recognition

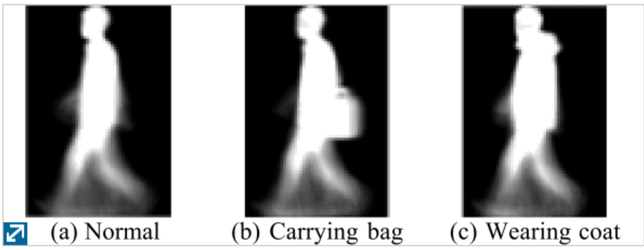


Fig 5.1 Different cases of GEI Variation

Fig 5.2 Process of GEI

Fig 5.3 Actual GEI Result

Chapter 6

Machine Learning

6.1 Introduction to Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly

6.2 Supervised Learning

Supervised machine learning algorithms can apply what has been learned in the past to new data using labeled examples to predict future events. Starting from the analysis of a known training dataset, the learning algorithm produces an inferred function to make predictions about the output values. The system is able to provide targets for any new input after sufficient training. The learning algorithm can also compare its output with the correct, intended output and find errors in order to modify the model accordingly. Supervised learning is further classified into two categories

6.2.1 Regression

- A regression problem requires the prediction of a quantity.
- A regression can have real valued or discrete input variables.
- A problem with multiple input variables is often called a multivariate regression problem.

6.2.2 Classification

- A classification problem requires that examples be classified into one of two or more classes.
- A classification can have real-valued or discrete input variables.
- A problem with two classes is often called a two-class or binary classification problem.
- A problem with more than two classes is often called a multi-class classification problem.
- A problem where an example is assigned multiple classes is called a multi-label classification problem.

6.3 Unsupervised Learning

In contrast, unsupervised machine learning algorithms are used when the information used to train is neither classified nor labeled. Unsupervised learning studies how systems can infer a function to describe a hidden structure from unlabeled data. The system doesn't figure out the right output, but it explores the data and can draw inferences from datasets to describe hidden structures from unlabeled data**.**

<u>Since Our dataset contains categorical values and the output contains discrete classes therefore our problem is classification problem.</u>

Chapter 7

Classification Algorithms

7.1 Decision Tree

A **Decision tree** is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements.

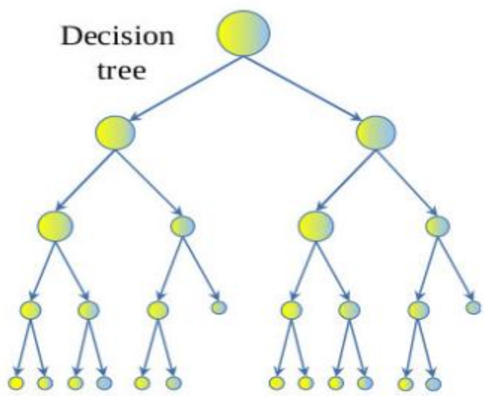


Fig 7.1 Decision Tree Illustration

Decision trees are commonly used in operations research, specifically in decision analysis, to help identify a strategy most likely to reach a goal, but are also a popular tool in machine learning.

A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.

In decision analysis, a decision tree and the closely related influence diagram are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated.

A decision tree consists of three types of nodes:

1. Decision nodes – typically represented by squares
2. Chance nodes – typically represented by circles
3. End nodes – typically represented by triangles

Decision trees are commonly used in operations research and operations management. If, in practice, decisions have to be taken online with no recall under incomplete knowledge, a decision tree should be paralleled by a probability model as a best choice model or online selection model algorithm. Another use of decision trees is as a descriptive means for calculating conditional probabilities.

Decision trees, influence diagrams, utility functions, and other decision analysis tools and methods are taught to undergraduate students in schools of business, health economics, and public health, and are examples of operations research or management science methods.

7.2 Random Forest

A Random Forest is a data construct applied to machine learning that develops large numbers of random decision trees analysing sets of variables. This type of algorithm helps to enhance the ways that technologies analyse complex data. Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction. One big advantage of random forest is, that it can be used for both classification and regression problems, which form the majority of current machine learning systems. Random Forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model. Therefore, in Random Forest, only a random subset of the features is taken into consideration by the algorithm for splitting a node.

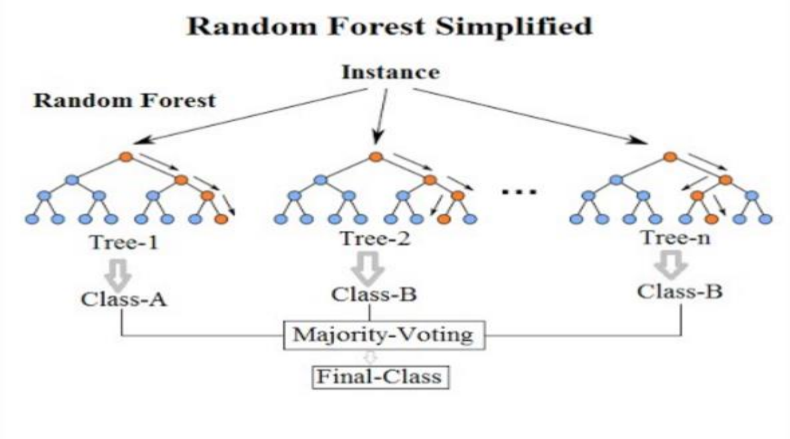


Fig 7.2 Random Forest Illustration

7.3 K-Nearest Neighbors (K-NN)

The K-Nearest Neighbors (K-NN) is a popular method of classification in machine learning. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. This value is the average of the values of its k nearest neighbors. Therefore, it classifies test data by finding the most similar data points in the training data, and making an educated guess based on their classifications.

KNN makes predictions using the training dataset directly. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances. For regression this might be the mean output variable, in classification this might be the mode (or most common) class value.

To determine which of the K instances in the training dataset are most similar to a new input a distance measure is used. For real-valued input variables, the most popular distance measure is Euclidean distance.

Euclidean distance is calculated as the square root of the sum of the squared differences between a new point (x) and an existing point (xi) across all input attributes.

Euclidean Distance (x, xi) = sqrt (sum ((xj – xij) ^2))

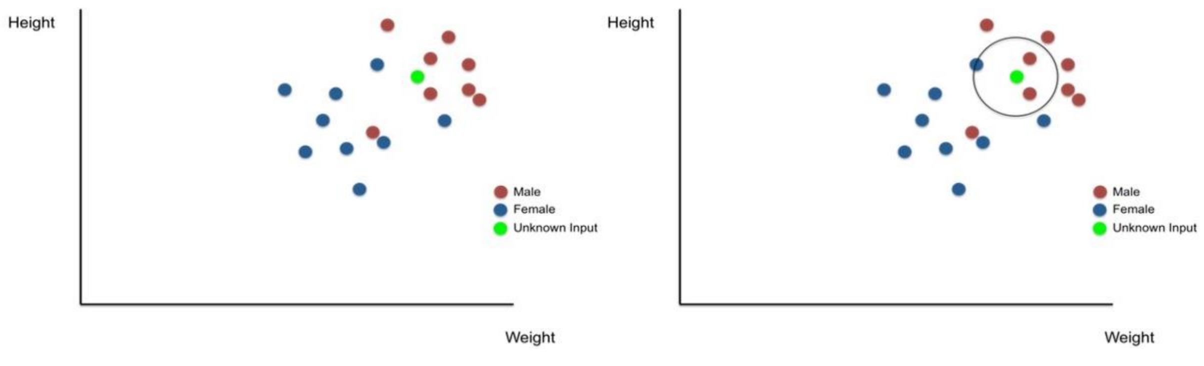


Fig 7.3 K-nearest neighbours Illustration

Chapter 8

Implementation and Result Analysis

8.1 Implementation

- Importing libraries like numpy, matplotlib.pyplot and pandas.
- Calculation of Gait Cycle
- Calculation of Gait Energy Image using numpy arrays and Gait Cycle
- Creating Dataset using os tools in python and numpy libraries
- Importing the Dataset.
- Dataset handling and removing noises using pandas in python.
- Importing the sklearn.linear_model library and fitting Logistic Regression to training data.
- Importing the sklearn.svm library and fitting Support vector machine to training data.
- Importing the sklearn.neighbors library and fitting K-Nearest Neighbours to training data.
- Importing the sklearn.tree library and fitting Decision Tree to training data.
- Importing the sklearn.ensemble library and fitting Random Forest to training data.
- Testing the classifiers of different models to the training data and predicting the accuracies.
- Testing the classifiers of different models to the testing data (new data).
- Plotting the confusion matrix for analysing correct/incorrect results.
- Plotting ROC for analysing the confusion matrix
- Plotting the bar graphs showing comparison of accuracies and variance of different models.

8.2 Result Analysis

8.2.1 Performance Measure

K-Nearest Neighbors

Test Set Accuracy- 92.22%

Decision Tree

Test Set Accuracy-59.6 %

Random Forest

Test Set Accuracy- 78.8% (without n_estimators)

Test Set Accuracy- 90.12% (with n_estimators=30)

8.2.2 Comparative Analysis

8.2.2.1) BAR PLOT

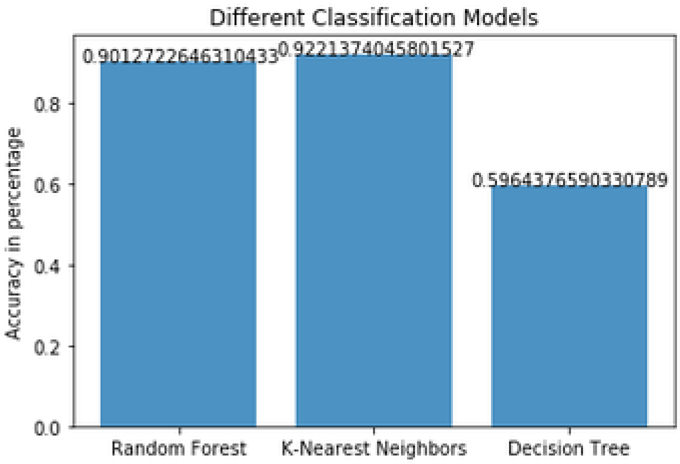


Fig 8.1 Comparative Analysis Bar Chart

Discussion:

The above results conclude that the Random forest and KNN are better and efficient classifier in classifying persons than Decision Trees

This can be due to decisions contained in the decision tree are based on expectations, and irrational expectations can lead to flaws and errors in the decision tree. Although the decision tree follows a natural course of events by tracing relationships between events, it may not be possible to plan for all contingencies that arise from a decision, and such oversights can lead to bad decisions.

8.3 Identification Result

8.3.1 Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. **The confusion matrix shows the ways in which your classification model is confused when it makes predictions**.

It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

The predicted classes are represented in the columns of the matrix, whereas the actual classes are in the rows of the matrix. We then have four cases:

• True Positive (TP) : Observation is positive, and is predicted to be positive.
• False Negative (FN) : Observation is positive, but is predicted negative.
• True Negative (TN) : Observation is negative, and is predicted to be negative.
• False Positive (FP) : Observation is negative, but is predicted positive.

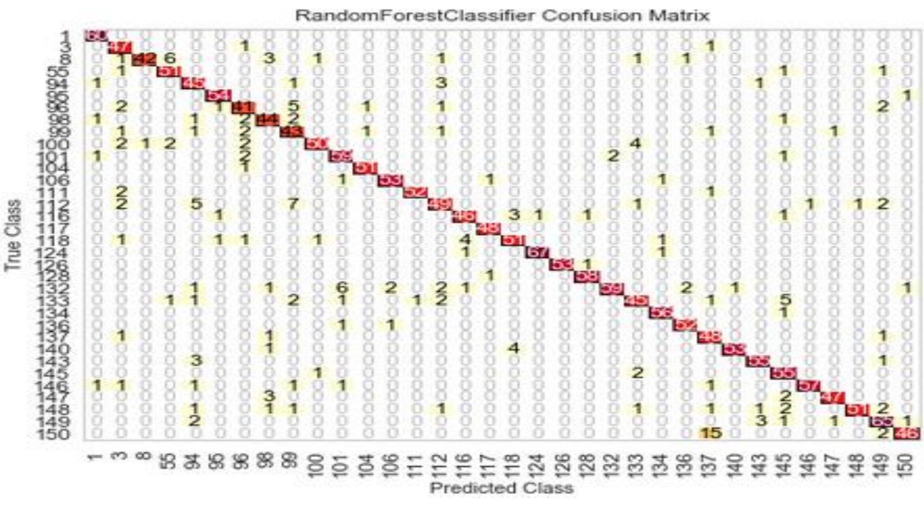


Fig 8.2 Confusion Matrix of Random forest Classifier

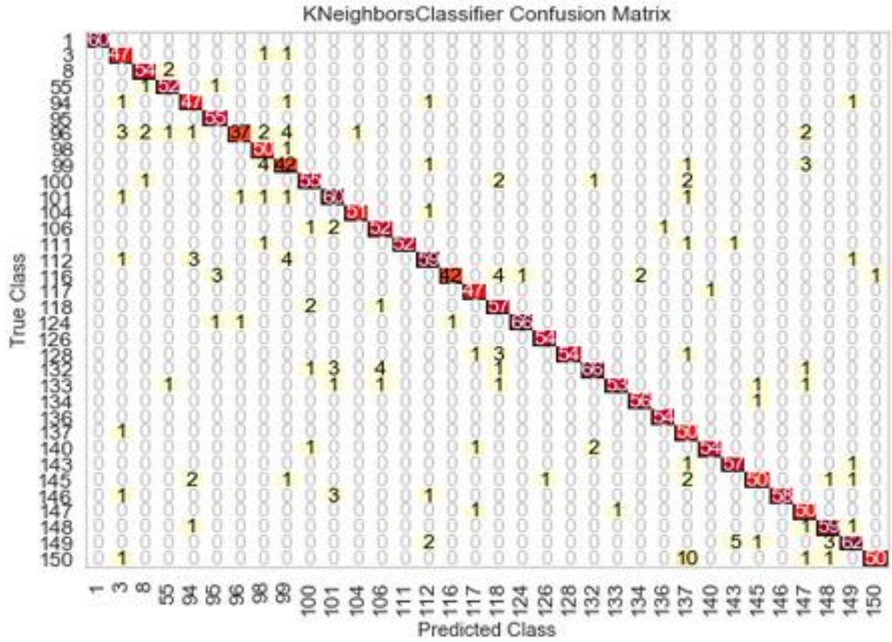


Fig 8.3 Confusion Matrix of KNN Classifier

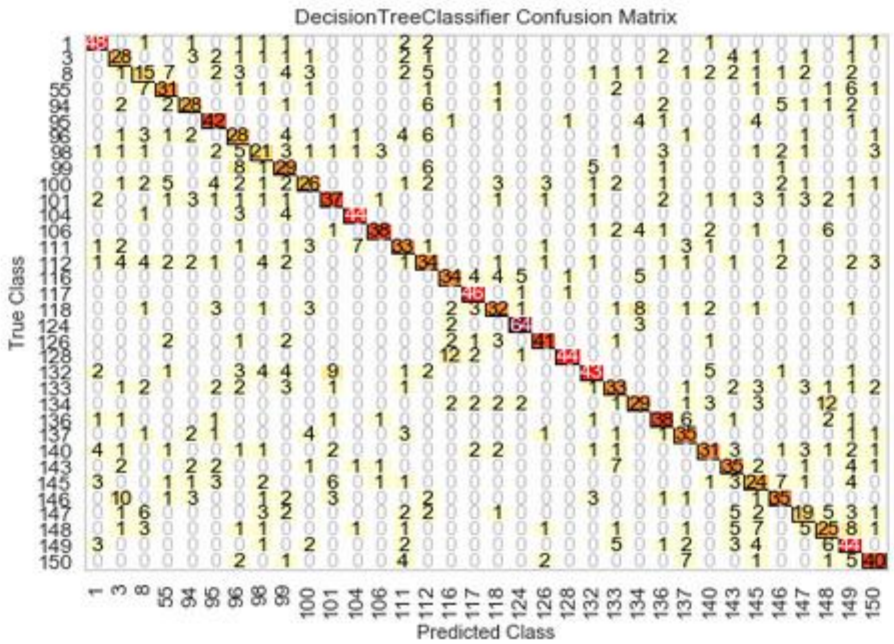


Fig 8.4 Confusion Matrix of Decision Tree Classifier

8.3.1.1 Discussion:

In the above graphs we see that the classifier models confuse while predicting a person's class

The above results show that the Decision Tree Classifier is having more problems than others in detecting the person's class

This mainly is due to:

Low recall, low precision: This shows that we miss a lot of positive examples and there are a lot of false positives.

Recall can be defined as the ratio of the total number of correctly classified positive examples divide to the total number of positive examples.

The value of precision we divide the total number of correctly classified positive examples by the total number of predicted positive example

8.4 Verification Analysis

8.4.1 ROC (Receiver operating characteristics)

AUC - ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represent degree or measure of separability. **It tells how much model is capable of distinguishing between classes.** Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, Higher the AUC, better the model is at distinguishing between patients with disease and no disease.

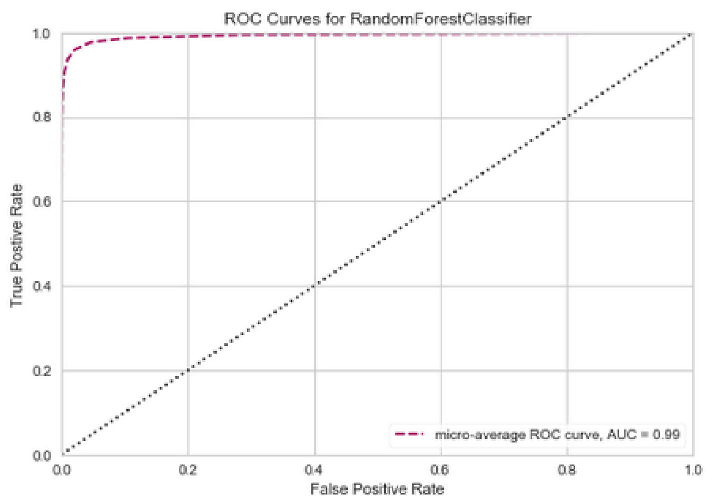


Fig 8.5 ROC verification for Random forest classifier

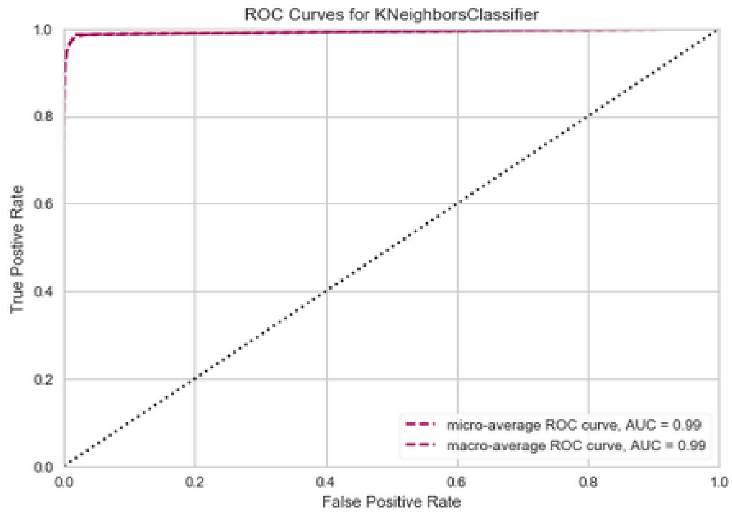


Fig 8.6 ROC verification for KNN classifier

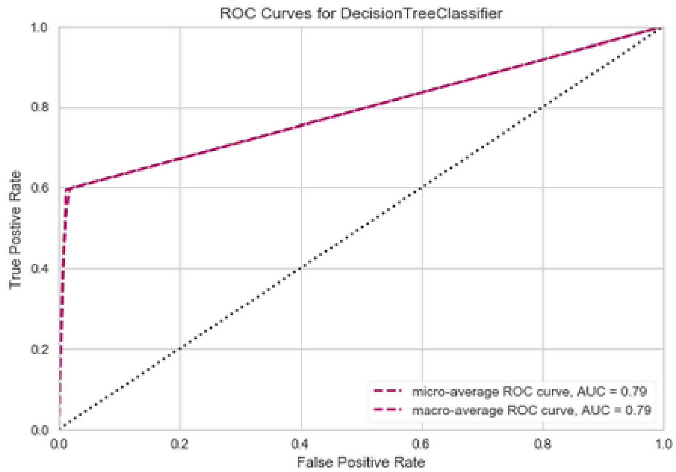


Fig 8.7 ROC verification for Decision Tree classifier

8.4.1.1 Discussion:

In the above results we conclude that the ROC-AUC of the Decision tree Classifier is not up to mark as expected.

The area under the ROC curve (usually denoted by **AUC**) is a good measure of the performance of the classification algorithm. If it is near 0.5, the classifier is not much better than random guessing, whereas it gets better as the area gets close to

This is mainly due to:

The TPR (True Positive Rate) only depends on positives, ROC curves do not measure the effects of negatives. The area under the ROC curve (AUC) assesses overall classification performance. AUC does not place more emphasis on one class over the other, so it does not reflect the minority class well.

Chapter 9
Conclusion and Future Scope

9.1 Conclusion

We have presented a simple representation of human gait appearance based on moments computed from the silhouette of the walking person for the purpose of person identification and classification. Our representation is rich enough to show promising results in these tasks. We have described the characteristic behaviours of model free gait features, one based on GEI of gait cycle of the silhouettes.

Experimental results show that

1. GEI is an effective and efficient gait representation as the classifier projected great results
2.The proposed recognition approach achieves highly competitive performance with respect to the published major gait recognition approaches

This view and appearance of model free structure of gait can be further extended to accommodate a multiple appearance model of a person and in conjunction with other recognition modalities.

9.2 Future Scope

In future we tend to enlarge the database to include more data of different time, outdoor environment, other sensors etc.

Further research on machine learning classifiers like:

1. "Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a coordinate
2. Convolution Neural Networks i.e. CNN for training and classification for better accuracy
3. Working on model-based approaches for gait recognition
4. Use of Gait Gaussian Image (GGI), Gait Entropy Image (GEnI) for Gait Feature Extraction

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Appendices

- **Gait Gaussian Image (GGI):** An image extraction technique in which fuzzification of pixels is done using Gaussian membership function, by considering mean and variance of the vector.

- **Gait Entropy Image (GEnI):** In Image processing, Entropy is defined as corresponding states of intensity level which individual pixels can adapt. It is used in the quantitative analysis and evaluation image details this entropy image calculated over a gait cycle is known as Gait entropy image

- **Convolution Neural Networks:** A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

- **Binarization:** Image binarization is the process of taking a grayscale image and converting it to black-and-white, essentially reducing the information contained within the image from 256 shades of gray to two: black and white, a binary image

- **Temporal Median Filter:** each background pixel is firstly modeled with a probability density function (PDF) learned over a series of video sequence. Then, pixels in video sequence with low probabilities are filtered, taken as foreground moving objects or noises. Finally, a temporal median filter is employed on video sequence, with pixels left.