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Identity Recognition of Humans in Video Surveillance System Using Cumulative Foot Pressure Images

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ABSTRACT

In recent years, security has become a major concern. The majority of the security systems consist of fingerprint and face recognition. But there is another form of security that is less discussed i.e. Gait recognition, which is identifying a person by his walking style and foot pressure images. In this paper, we focus on the ground response force which can be utilized to tell the difference in human gaits. The floor-sensor-based image is a two-dimensional image that collects the geographical and historical parameters of ground response force during a single gait cycle. The proposed model is trained on the standard dataset i.e. CASIA -D. The proposed work will demonstrate how these CFPI can be used to identify an individual in many cases such as homeland security, secret lockers in banks. It also helps us in the medical field for injury prevention and diagnosing lower limb problems etc.

Keywords- Gait, Security, Floor-sensor, CASIA

1. INTRODUCTION

Biometrics is a strong way for dependable human identification that utilizes human physiology or behavioral traits such as the face, iris, fingerprints, and hand shape. These biometrics approaches, on the other hand, are restricted to several controlled situations. Most face recognition algorithms, for example, can only recognize frontal or nearly frontal faces; other biometrics, like fingerprints and iris, are no longer valid when a person arrives unexpectedly in surveillance. As a result, many surveillance applications, particularly at a distance, require novel biometrics recognition algorithms.

Gait is one of many physical and behavioral characteristics that can be used to identify someone. People can be recognized using their stride characteristics and foot pressure images, which have applications in homeland security, bank secret lockers, access control, and human-computer interfaces. While most studies on human identification using gait features have focused on computer vision-based algorithms, there have been studies on gait recognition using foot pressure data. The gait of a person refers to how they walk. Gait recognition tries to solve this challenge by recognizing persons from a distance based on their walking patterns and foot pressure images. Many studies have demonstrated the value of using gait information in biometrics to distinguish between people. Gait features are used to identify suspects based on their walking patterns, even in criminal cases. Ground response force and cumulative foot pressure images are not as popular in the pattern recognition and image processing fields as limb movement recovered from video-based gait extraction approaches. Because it only provides an approximate distribution of foot pressure, identifying an individual using foot pressure data is difficult.

2. LITERATURE SURVEY

Human gait was discovered to have 24 separate components in early medical and psychological investigations [1][2], which may be utilized to identify an individual. It was discovered that light pointers attached to an individual's joints may be utilized to represent human motions and that point-light displays can be used to distinguish human activities [3]. According to the aforesaid research, each person has a distinct muscular-skeletal structure that might be utilized to identify him or her. As a result, gait recognition is a possibility. This survey aims to provide comprehensive, up-to-date research and analysis data on gait-based authentication breakthroughs and current practice. The following section presents some of the past work in this area.

- The authors proposed the first gait recognition system in Reference [7], which is related to a tiny gait repository. Following that, the Defense Advanced Research Projects Agency (DARP) launched the well-known Human ID initiative, which was the first openly available database for gait identification. Later several academics have worked on human gait identification in a variety of ways. Gait recognition has recently been accomplished using sensor data from accelerometers, floor sensors, and other devices.
- The Authors[8] were the first to use a model-based approach to feature depiction. Ben Abdelkaderet al. [8] used structural stride parameters of people to simulate the human body. The stride length (in meters) and cadence (steps per minute) are calculated from the vision-based gait system for identifying persons.
- Tanawongsuwan and Bobick [11] used joint angles to simulate the human body. They conducted the study by extracting the angle of joints derived from gait data and utilizing joint angle curves to identify individuals.
- Simultaneously, because human legs are so important in determining gait, several studies have focused on leg models. For example, Yam et al. created human legs and used them to research walking and running techniques.
- For the first time, Nakajima et al. used ground sensors to collects trials of gait data, such as pressure. It uses continuous wave radar to gather data on human gait.
- According to research presented at the Norsk Information security conference in 2010, the wearable sensor-based gait technique is the newest, aside from machine vision (MV) and floor sensor (FS) based gait recognition. It operates by attaching motion recording sensors to various parts of a person's body, including the waist, pockets, and shoes. Wearable sensors (WS) can be used for a variety of purposes since they retrieve a wide range of data. Different types of sensors, such as accelerometers, gyro sensors, force sensors, and so on, are currently in use, although the majority of the research to date has focused on accelerometer-based gait detection. According to research presented at the Norsk Information security conference in 2010, the wearable sensor-based gait technique is the newest, aside from machine vision (MV) and floor sensor (FS) based gait recognition. It operates by attaching motion recording sensors to various parts of a person's body, including the waist, pockets, and shoes. Wearable sensors (WS) can be used for a variety of purposes since they retrieve a wide range of data. Different types of sensors, such as accelerometers, gyro sensors, force sensors, and so on, are currently in use, although the majority of the research to date has focused on accelerometer-based gait detection. The picture improvement and feature extraction stages are primarily concerned with the distinct qualities of foot shape, durability, and distinctive properties, all of which are explained. The primary issues that were discussed were collectability and generality. Gait Recognition could be a powerful signal processing method for biometric identity verification [6].
- Model-based feature representation approaches for gait identification often use the physical body's distances or joint angles after modeling the full physical body. To partition the human body, Bobick and Johnson used four basic distances: head-pelvis, head-foot, and foot-pelvis, as well as left-right foot distances.
- Nakajima et al. [10] normalized the input raw footprint in five phases. As a result, the impact of footprint location and orientation was reduced, and the recognition rate increased from 30.45% to 85.00%. Learning with a Focus on Distinction Sultana and Ronning [14] created a categorization algorithm for footsteps called Vector Quantization (DSLVQ). By combining the LVQ approach with other classifiers, they were able to enhance the recognition rate [15]. Middleton et al. set out to create a low-cost gait identification system based on floor sensors. Orr and Abowd [13] demonstrated that the impact of footwear could be ignored. Jenkins and Ellis [11] wanted to use footfall to derive body mass information.

3. METHODOLOGY

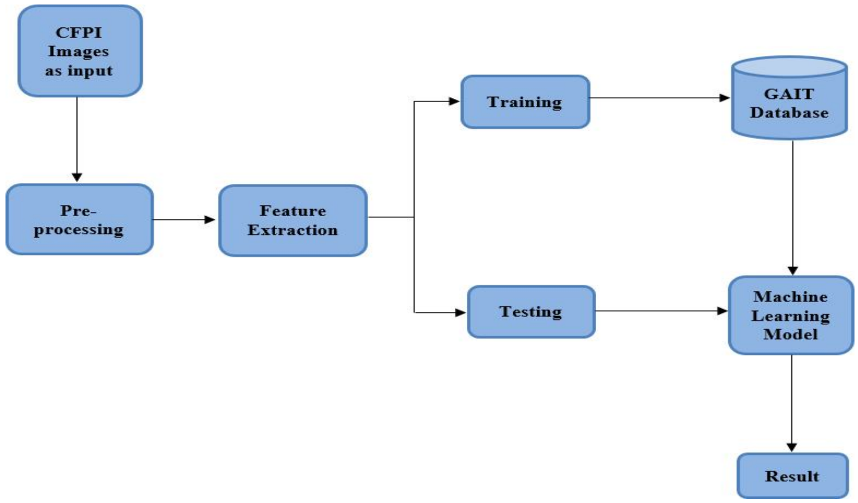


Fig:1: Proposed Methodology

3.1 Data Acquisition

- Sensors, which convert physical properties to electrical impulses, are among the components of data acquisition systems.
- Circuitry for signal conditioning, which converts sensor signals into a format that can be converted to digital values.
- Analog-to-digital converters, which transform conditioned sensor signals into digital values.

The Proposed work is on the Standard Data set i.e. CASIA-D dataset which consists of 88 subjects.

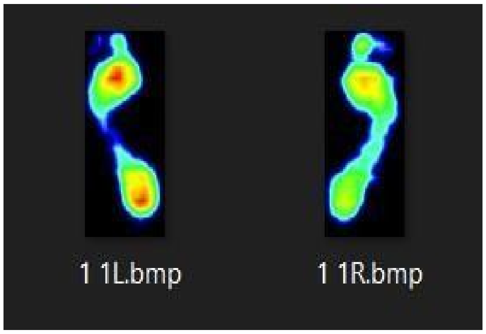


Fig 2: Sample Dataset

3.2 Data Pre-processing Resizing:

In computer vision, resizing images is an important pre-processing step. In general, our machine learning model performs better on smaller images. With a twice-as-large input image, our network must find information from four times as many pixels, which takes time.

3.2.1. Conversion from RGB to Grayscale Image:

The Average Method:

As the grayscale value, the Average technique uses the average value of R, G, and B.

(R + G + B) / 3 = grayscale

The formula is 100 percent true in theory. When writing code, however, you may encounter an uint8 overflow error, which occurs when the total of R, G, and B exceeds 255. R, G, and B should be calculated separately to avoid the exception.

$R / 3 + G / 3 + B / 3 = \text{Grayscale}$

The standard method is easy, but it does not perform as well as it should. The reason for this is that human eyes react to RGB in different ways.

The Weighted Method:

The luminosity approach, also known as the weighted method, balances red, green, and blue colors based on their wavelengths. The following is the new formula:

$0.299R + 0.587G + 0.114B = \text{grayscale}$

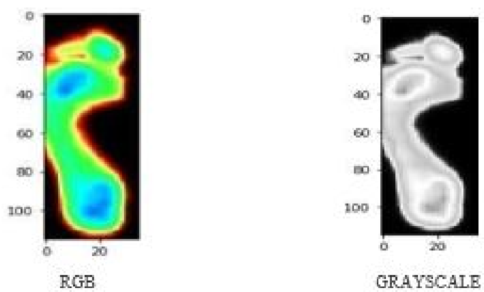


Fig:3: RGB and Grayscale Image

3.3 Feature Extraction

3.3.1.Grayscale pixel values as features

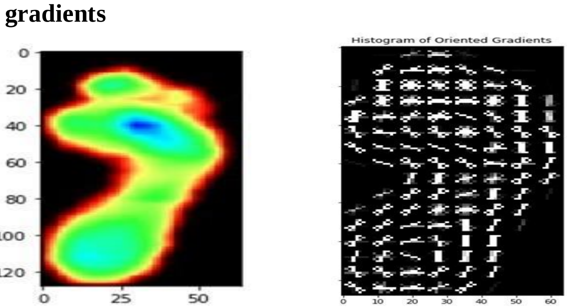
The simplest method for constructing features from a picture is to use the raw pixel values. Machines can see any image within a matrix of numbers. The size of this matrix is determined by the number of pixels in the input image. The Pixel Values of each pixel represent or describe how bright it is and what color it should be. In the simplest instance of binary images, the pixel value may be a 1-bit number indicating foreground or background. Pixel values are numbers that represent the brightness or intensity of a pixel. Smaller numbers closer to zero help to depict black, whereas larger numbers further away from zero help to represent white. A value closer to 255 is used to symbolize white. As a result, the concept of pixels and how a machine views pictures through numbers rather than its eyes is commonly used. Three channels make up a color image: red, green, and blue. The color intensity of each pixel is represented by the matrices of each channel, which have values ranging from 0-255.

$$\text{sizegroup1}+\text{sizegroup2}+\text{sizegroup3}=m\times n+m\times n+m\times n=3\times m\times n$$

So our generic formula would be:

$$m\times n+m\times n+C(m\times n,2)=2m\times n+C(m\times n,2)$$

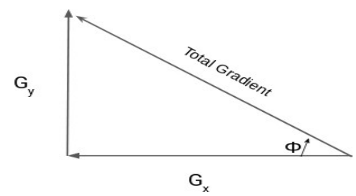
3.3.2 Histogram of Oriented gradients



3

Fig:4: HOG

Another method that can be used is HOG. To extract features from picture data, the Histogram of Oriented Gradients feature descriptor is widely utilized. It's commonly used in computer vision for object detection. The HOG feature descriptor counts how many times a gradient orientation appears in a certain area of a photograph. The structure or shape of an object is the emphasis of the HOG description. The edge direction can also be provided using HOG. This is done by extracting the gradient and orientation of the sides (or magnitude and direction). In 'localized' parts, their orientations are likewise specified. This means that the entire image is weakened into smaller regions, each having its gradients and orientation. We'll go over this in further detail in the parts that follow. Finally, for each of these sections, the HOG would build a separate Histogram. The histograms are created using the gradients and orientations of the pixel values, hence the term "Histogram of Oriented Gradients.



The Histogram of Oriented Gradients Calculation Process (HOG) is as follows,

The base and perpendicular gradients are used here.

To compute the total gradient magnitude, use the Pythagoras theorem: Total Gradient Magnitude = $\sqrt{[(G_x)^2+(G_y)^2]}$

Then, for the same pixel, determine the orientation (or direction). We already know how to write the tan for the angles: $\tan(\Phi) = Gy / Gx$

Hence, the value of the angle would be:

$\Phi = \mathrm{atan}(Gy / Gx)$

3.4.Model Design

3.4.1 SVC (support vector classifier)

The proposed system uses SVM for classifying the individuals In SVC, data points are mapped from data space to a high dimensional feature space using a kernel function. The algorithm searches the kernel's feature space for the smallest sphere that encloses the image of the information using the Support Vector Domain Description algorithm. This sphere provides a set of outlines that encircle the data points when projected back to data space. SVC links the points enclosed by each contour with a comparable cluster after reading these contours as cluster boundaries.

The contours where f(x)=0 are then interpreted as cluster boundaries. An example of such contours is shown in Figure 5. However, these boundaries define the clusters implicitly, and a further step is required to "tease" the cluster membership out of the SVDD.

1, if f(x)>0 for all x on the line segment connecting xi and xj 0, otherwise

Ai j =

In conjunction with the Russian kernel, SVC employs SVDD to construct non-linear cluster boundaries:$k(x,x')=\exp(-\gamma\|x-x'\|2)$.

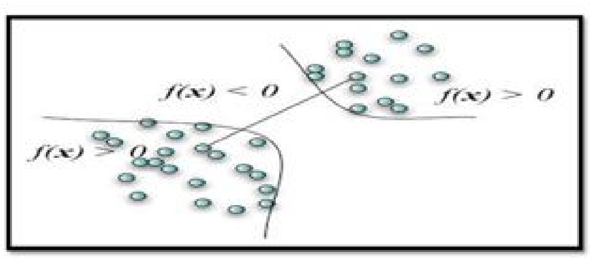


Fig 5: The line segment connecting points in different clusters must pass through a low-density data space region where the SVDD gives a negative value

A choice function in SVDD determines whether a given input is inside or outside the feature-space sphere, indicating whether or not a given point is part of the distribution's support. It's the radius-squared of the feature-space sphere minus the distance-squared of the image of a knowledge point x from the center of the feature-space sphere. This function returns a positive value if x is inside the feature space sphere; otherwise, it yields a negative value. For additional information about SVDD, the reader suggested reading the SVDD article.

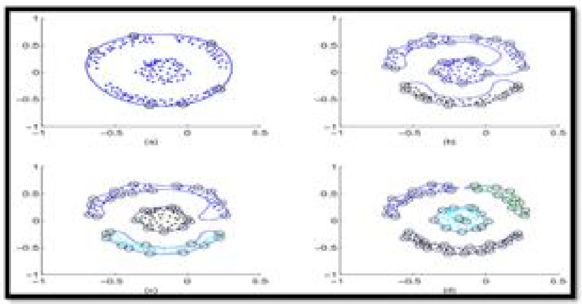


Fig 6: Contours generated by SVDD as γ is increased.

4. RESULTS AND DISCUSSIONS

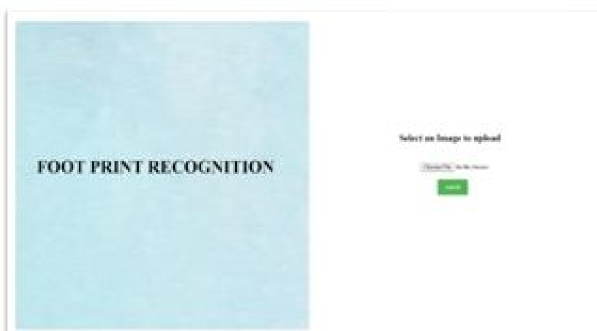


Fig 6: This is the user home page of web interface built by using flask framework & HTML/CSS here user select an image from the dataset then click on submit button, after this, the image will undergo pre-processing then model will classify it and predict the result below which contains the label name of the foot pressure image.

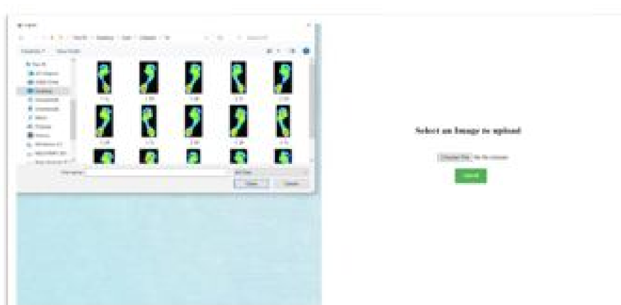


Fig 7: This is the Selection page where the user clicks on choose file button it will be redirected to the file manager window from this user select image from the dataset folder and upload it for prediction.

Fig 8: This is the Result page after uploading the image from the dataset and the model will classify it and produce the result here user knows the label name of the unknown image of foot pressure as shown above.

Method	Number of Samples	Accuracy
Our method	2640	87.48192771
Reference [10]	110	85
Reference [14]	200	65.8–70.2
Reference [15]	440	79.2–98.2
Reference [12]	360	80
Reference [11]	62	39

Table1: Comparison of the works

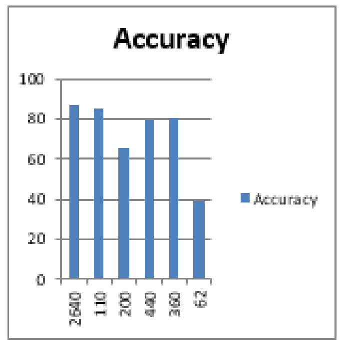


Fig:9:Analysis of the works

The accuracy of classification models is one of the factors to consider when evaluating them. Informally, accuracy refers to our model's percentage of true predictions. The formal definition of accuracy is as follows:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

The following formula can be used to calculate accuracy in terms of positives and negatives for binary classification:

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

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

After building the model by applying foot pressure images and trained the algorithm SVC (support vector classifier) it produces theaccuracy of unknown data is 87.4819277.

5. CONCLUSION

The literature review helped us understand the scope of gait recognition in a biometric system. It was identified that a lack of accurate and reliable solutions for CFPI based biometric systems and thus the problem was formulated. We proposed a system on Cumulative Foot Pressure Images (CFPI), to achieve good results, by developing an appropriate model using various tools and technologies. For computational efficiency, the suggested method employs a linear variant of the support vector classifier (SVC). This means that the traits we employed in our technique are mainly linearly separable.

6. FUTURE SCOPE

- Improving accuracy by using some variations or modifications for the existing model.

- Using ANN and Deep learning to obtain more accurate predictions with a considerably large dataset.
- Implementation of human identification using CFPI techniques on real-time data.
- The ground reaction force of real-time data can be used to calculate pressure applied on the foot of a person.
- Provide security measures to avoid misuse of technology.

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