

A Review on Deep Learning Classification Techniques for Gait Recognition on Humans

¹Umamaheswari N, ²Saranya R, and ³Shanmugapriya K

¹ Faculty of computer science and engineering, R.M.K College of engineering and technology
Puduvoyal, Tamil Nadu, India, Email: umamaheswaricse@rmkcet.ac.in

² Faculty of computer science and engineering, R.M.K College of engineering and technology
Puduvoyal, Tamil Nadu, India, Email: saranyacse@rmkcet.ac.in

³ Faculty of computer science and engineering, R.M.K College of engineering and technology
Puduvoyal, Tamil Nadu, India, Email: shanmugapriyacse@rmkcet.ac.in

ABSTRACT

Gait recognition is the process of identifying people based on their movements on foot or the way they walk without their co-operation or their permission. Gait is found to be less unremarkable since it can identify the person from a distance. This paper provides a review of algorithms used for classification technique in gait recognition, real-time case studies for backpropagation and SVM classifier, and recent developments in Gait recognition. Generally, a gait recognition system deals with training and testing phases. These two phases pass through different stages as pre-processing, feature extraction, and classification. The conclusion deals with the accuracy result of many classification techniques used in gait recognition, and also future directions are discussed.

Keywords: *SVM classifier; Pre-processing; Feature Extraction.*

1. INTRODUCTION

In this fast-moving world, identifying an individual is an essential and challenging task in many fields to prevent fraudulent activities in banking and security fields. Many biometric techniques have been emerging over the years for identifying individuals with several unique characteristics. Attention and co-operation are necessary for these biometric activities. Biometric characteristics are of two types; one is physiological, and the other is behavioral.

The physiological characteristics include the face, iris, palmprint, hand geometry, retina recognition, etc. The behavioral characteristics include gait analysis, voice ID, mouse use characteristics, etc. Since physiological characteristics need user co-operation and do not show accurate results with low resolution, gait recognition is more attractive nowadays. Gait recognition is the biometric technology that is used to monitor the person without their co-operation. Gait recognizes every person's style of walking as it's unique. This walking style helps in human identification.

The system will identify the individual by comparing his gait in the dataset. Every recognition deals with pre-processing, feature extraction, and classification. There are several classification techniques to classify gait patterns. Further gait features differ from different view angles [1], speed variations, signature formation, etc.

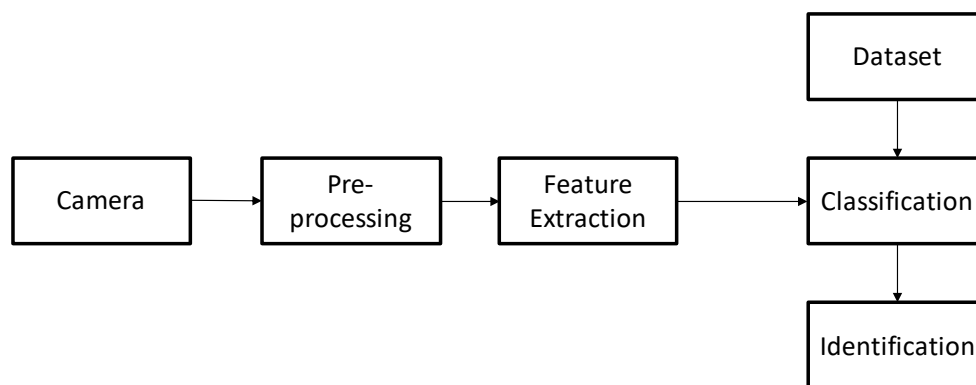


Figure1: General description of gait recognition

In Figure 1, the person's movement is being captured from the camera. These videos are pre-processed so that the unwanted data are removed from the video. Features are extracted from the pre-processed image. Then the classification technique is used to identify the person. Here the backing dataset is used to compare the individual gait and provide accurate results.

2. CLASSIFICATION OVERVIEW

The final stage of gait recognition is the classification. It is computed between the testing and training features to determine the accuracy of the proposed model. In this paper, many classification algorithms which come under supervised machine learning. Deep learning, supervised machine learning, distracting more attention on specialists in gait recognition to mark it appropriately, in a real-time environment.

2.1 Bayesian networks

The term Bayesian network was introduced by Pearl in 1985 to emphasize the basics of the Bayesian network for updating information[2]. Also, it provides the difference between causal and evidential modes. In an intelligent and expert system, probabilistic reasoning summarized their properties in the late 1980s by Pearl and Neapolitan.

A Bayesian network is a probabilistic graphical model. It can be widely used in detection, diagnostics, and decision-making. Bayesian networks help to maintain a conditional sequence in the directed graph. Through the relationship, it can inference the random variables [3]. This way of multivariate chance distributions is observed as casual networks. Each variable z_i is a vertex in a directed acyclic graph. The factored form of probability function $P(z_1, z_2, z_3, \dots, z_n)$ is as follows.

$$P(z_1, z_2, z_3, \dots, z_n) = \prod_{i=1}^n P(z_i | \Pi_{Z_i}). \quad (1)$$

Π_{Z_i} is the set of vertices

Bayesian network is generally used for prediction purposes. It predicts more outcomes for each possible observation [3]. Accuracy is found to be 88.29-90.2% [4].

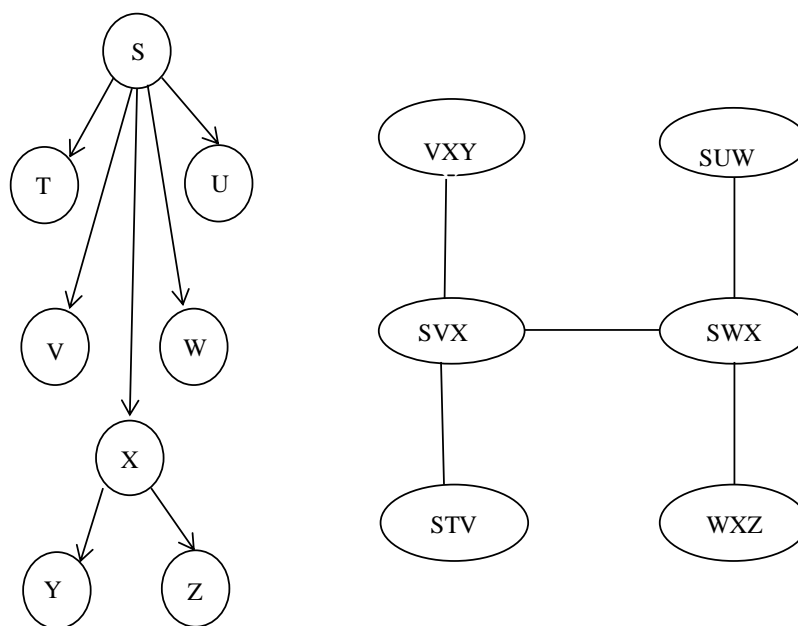


Figure 2. Bayesian network and tree structure

Figure 2 shows the corresponding tree of clusters, and it is known as tree decomposition. This tree cluster consists of a set of variables in the network. The tree clusters help pass messages. However, these sizes of a message depend on the size of clusters. Some clusters in the Bayesian network consist of nodes. To pass the message, it must satisfy some conditions in the algorithm.

- Every node and its parents must be appropriate to a particular tree cluster
- There is a graph-theoretic notion, recognized as treewidth, which sets a lower bound on the size of the largest cluster

2.2 SVM Classifier

This SVM algorithm was invented in 1963 by Vapnik and Chervonenkis [5]. In 1992, the kernel trick was applied to create the non-linear classifiers and is developed by Boser et al. These non-linear classifiers are generally used to maximize the hyperplane. Cortes and Vapnik invented the current soft margin classifiers in 1993 and are proposed by 1995.

An SVM classifier works on the fixed vector and in model identification. [6] Deals with the pattern recognition method to optimize the SVM using the PSO algorithm. The training and testing phase of sample data is optimized with the parameters and the kernel function. The vector values are extracted in rows and columns, respectively.

$$\dot{N}(i, j) = N(i, j) - \min(i) . \quad (2)$$

where N , \dot{N} is the scaled and unscaled vectors.

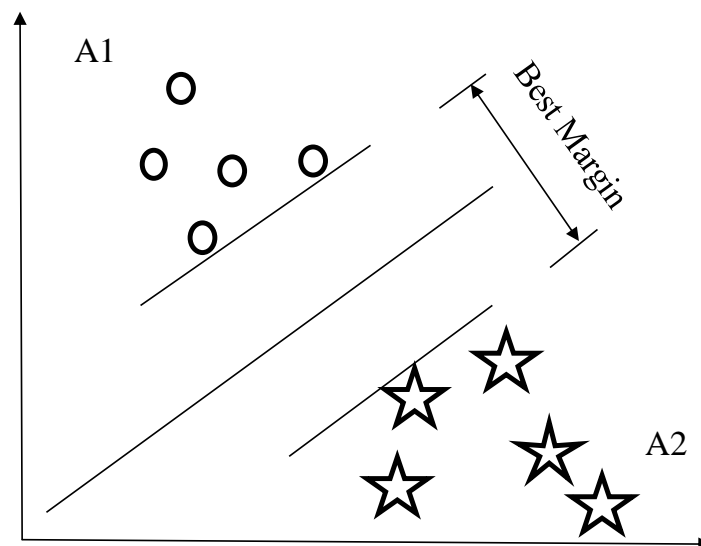


Figure 3. Dataset margin in SVM Classifier

In Figure 3, we can classify the dataset into two categories as A1 and A2. Define the values by $A1 = 1$ And $A2 = -1$. This is generally a binary classification problem. For instance, if our data points represent email texts, we wish to categorize them as spam and non-spam. The linear function in between ensures the best possible separation between the two categories. We will identify the separation between the categorized datasets as margin will be governed by the distance between the closest and the separating hyperplane. SVM is widely used in the application ranging from computer vision to NLP.

2.3 Naive Bayes

Bayes introduced Bayes theorem in the year (1702 -61). The name is used as 'Naive' because it requires the rigid independence assumption between input variables [7]. This theorem helps to compute the distribution of probability parameters of the binomial distribution. Price presents an essay towards solving the problem in the doctrine of chances in 1763.

The Naive Bayes algorithm is based on the principle of Bayes theorem. Bayes theorem functions on conditional probability. It is a family of an algorithm where all of them share the common principle. The dataset is divided as a feature vector and the response vector. Naive Bayes is generally used in a large volume of data [8]. It is a highly extensible algorithm, and it's famous for email spam classification.

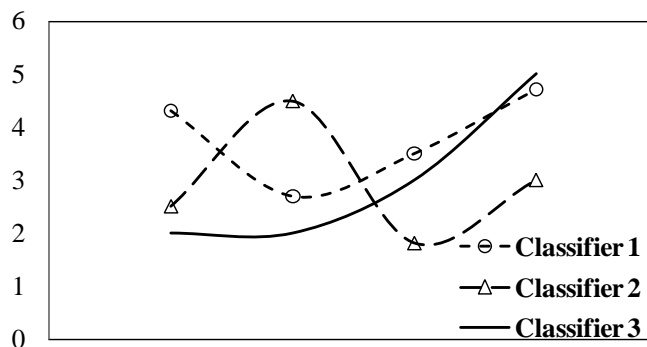


Figure 4. Naive Bayes algorithm

Received 25 April 2021; Accepted 08 May 2021.

In Figure 4, the Naive Bayes algorithm consists of a set of classifiers that works based on the principle of Bayes theorem. Here the goal of the Bayes theorem is to calculate the conditional probability. When a variable selection is carried out correctly, Naïve Bayes can perform as well as or even better than other statistical models. Naive Bayes requires a strong assumption of independent predictors.

2.4 SMO Algorithm

Platt is invented Sequential Minimal Optimization (SMO) in 1998 at Microsoft Research. SMO algorithm is used for solving the quadratic programming (QP) and for training the support vector machine [9]. In 1997, E. Osuna, et al. proved a theorem that suggests a whole new set of QP algorithms for SVMs.

Sequential minimal optimization (SMO) Algorithm is generally a decomposition algorithm as it decomposes multiple variables into sub-problems. Iteration is done by optimizing points [9]. These small sub-problems are calculated analytically to avoid time-consuming. The algorithm chooses the multipliers to accelerate the rate of convergence. These optimization problems help to find an analytical solution.

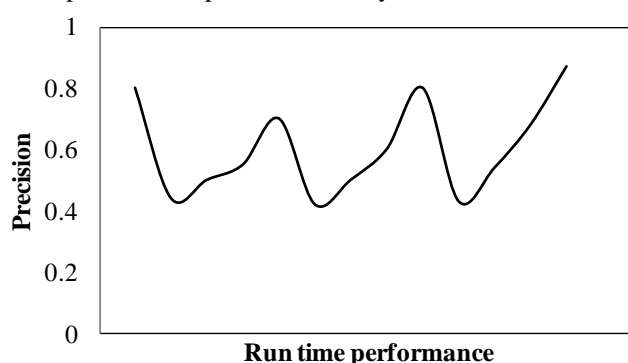


Figure 5. Running performance for SMO Classifier

In Figure 5, we can see significant advantages in balancing precision and running time. It considers each unique subset of the dataset. There will be 2^N subsets if there are initially N labels, which poses significant label costs in training iterations [10]. The curve represents running time in seconds. Algorithms should be carefully selected if running performance is also taken into account.

2.5 Backpropagation neural network

The term backpropagation and its general use in neural networks were announced in Rumelhart et al. in 1989 [11] and then elaborated in the paper called "Learning representations by back-propagating errors". This algorithm is used to train the neural network called chain rule. It is a standard method of training artificial neural networks. This method helps calculate the gradient of a loss function with respect to all the network weights.

Backpropagation neural networks are the supervised network that is used to train the neural networks. It helps to tune the weight for each node in the neural networks. It calculates the gradient of the loss function, and then feeding backward will happen through the function's derivatives. There is no particular order of updating the weight [12]. The gradient of the error function is computed and compute the gradient recursively. These neural networks can tackle intricate problems and provide accurate solutions.

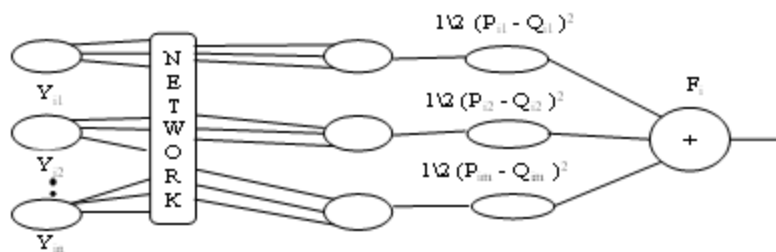


Figure 6. Backpropagation network model

In Figure 6, the network is initialized with randomly chosen weights. Every one of the j output units of the network is connected to a node that evaluates the function $1/2 (P_{ij} - Q_{ij})^2$, where P_{ij} and Q_{ij} denote the j^{th} component of the output vector P_i and of the target Q_i . The additional m nodes' outputs are collected at an anode, which adds them up and gives the sum F_i as its output. The same network extension has to be built for each pattern Q_i . A computing unit collects all quadratic errors and outputs their sum $F_1 + \dots + F_p$. The output of this extended network is the error function F .

2.6 Bat Algorithm

The Bat algorithm is a metaheuristic algorithm for global optimization. It was inspired by the echolocation behavior of microbats, with varying pulse rates of emission and loudness. The Bat algorithm was introduced in the year 2010 by Yang [13].

Bat Algorithm generally deals with the echolocation characteristics. Depend on the characteristics, the algorithm details as follows [14]. Generally, echolocation is a type of sonar that is used to detect prey by bats. Each bat is associated with the velocity u^r and the location y^r , where r is the iteration.

$$U_i^r = u_i^{r-1} + (y_i^{r-1} - y_*) g_i \quad (3)$$

$$Y_i^r = y_i^{r-1} + u_i^r \quad (4)$$

Where g_i is the difference between the maximum and minimum value of the random vector, each bat is associated with random frequency [15]. Thus, the BA algorithm's application is more efficient in classification fields and is more feasible in matching fields.

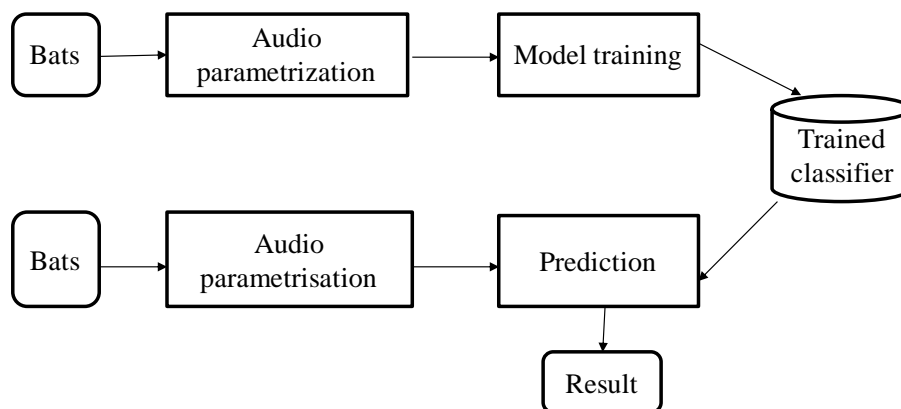


Figure 7. The process used for automatic classification using bat classifier

The testing on prediction models demonstrates the generated dataset performs well on predicting the call pulses and silent intervals. The filter bank used in this parameterization is the same as the one used to extract the features. The filters that comprise the filter bank are created using a linearscale, which means that all the centers are equally separated. That way, the frequencies below are not taken into consideration when parameterizing the signal. This is performed to avoid outside noise interference in our analysis. The samples length to parameterize has been studied according to the accuracy of the training results and testing the classifier.

2.7 Artificial Neural Networks

The history of neural networking arguably began in the late 1800s with scientific endeavors to study the human brain's activity [16]. In 1890, James published the first work about brain activity patterns. McCulloch and Pitts were introduced artificial neural networks in 1943. They introduced the computational model for neural networks called threshold logic. In 1949, Hebb published "The Organization of Behavior," which illustrated a law for synaptic neuron learning. In 1951, Minsky made the first Artificial Neural Network (ANN) while working at Princeton. In the year 1958, "The Computer and the Brain" were published, a year after Neumann's death. Neural networks are a set of an algorithm that is used to cluster and classify the raw input data. ANN is considered as a connection of nodes associated with weight. A Neural network consists of three layers called Input, hidden, and output [17]. The input layer feeds the raw data into the network, and the hidden layer generally deals and processes with the raw information fed by the input layer. There are one or more hidden layers in the neural networks. The output layer provides the processed data that is the desired output.

The first phase of the neural network is the training classifier. Training data are collected from the database [18], and are collected manually with several points. Then the second phase in a neural network is data clustering. In gait recognition, clustering depends on the walking style of humans. The classification accuracy of NN is found to be 89% [19] [20]. The feature extracted from the gait recognition is knee points, a position from both ankle and knee points. The algorithm is mainly implemented in Matlab. And the database used is the CASIA database.

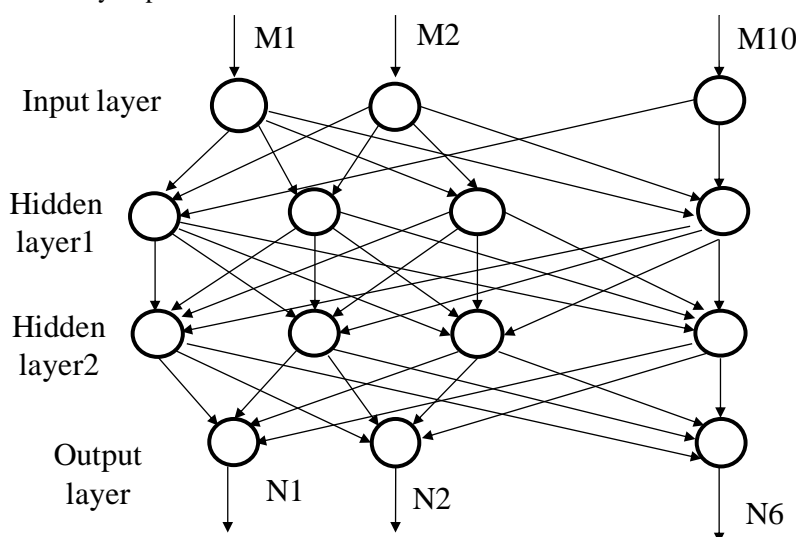


Figure 8. Neural network model

In Figure 8, the neural network classifier model to perform the classification task is a feed-forward the multilayer NN with two hidden layers. ANN is to learn and train a data set consisting of ten inputs [M1, M2, M10] and six binary outputs [N1, N2, N6], which clearly define the six different classes representing the six gait states [20]. ANN

Received 25 April 2021; Accepted 08 May 2021.

is a non-linear model that gives an excellent contribution to real-time problems. It is built gradually with the systematic procedure to improve the performance criterion following some internal constraints, which is known as the learning rule.

2.8 KNN classifier

K-nearest neighbor was introduced by Fix and Hodges in 1951[21]. Later in 1967, some of the formal properties of the k-nearest-neighbor rule were worked out. It was shown that for $k=1$ and $n \rightarrow \infty$, the k-nearest-neighbor classification error is bounded. Formal properties of k-nearest-neighbor classification were established. A long investigation ensued, including new rejection approaches by Hellman (1970) and fuzzy methods (Jozwik, 1983; Keller et al., 1985).

KNNclassifier is a simple classifier. It makes decisions based on the feature points that are selected from the video. In this biometric field, KNN sets the threshold value to get the neighbor's maximum possible distance[22]. The correct decision has been made from the fewer points of k. The decision has been made based on the $k \times v$ nearest neighbor majority value. The threshold value is defined as

$$t \theta_m = \theta * t_m \tag{5}$$

Where θ is the threshold value is the average distance between the points in m^{th} class. The number of prototypesshall be equal to the number of neighbors in the classifier. The θ can be carried with different values. Here in this KNN classifier, the accuracy is about 90 to 93%. The result obtained from this classifier shows a high potential for human gait.

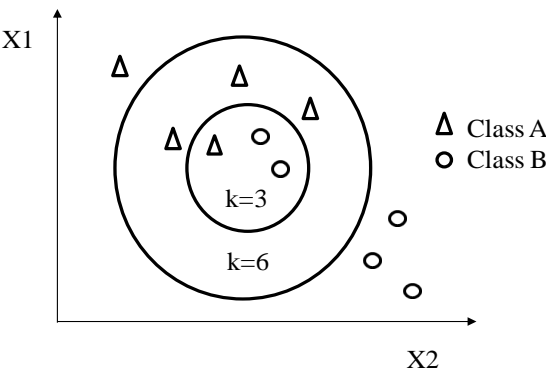


Figure 9. Classification using KNN algorithm

In Figure 9, you find the k closest point to the star and then classify points by majority vote of its k neighbors. Let's say, $K = 3$. Hence, we will now make a circle with BS as the center just as big as to enclose only three datapoints on the plane. The boundary becomes smoother with the increasing value of K. With K increasing to infinity, and it finally becomes all circle or all triangle depending on the total majority.

Table 1: Measurement of the performance of classifiers

Classification	Algorithm overview	Remarks	Accuracy percentage	References
Naïve Bayes	Naïve Bayes works on conditional probability. It's fast to predict class data sets.	It does not require as much training data. It handles both continuous and discrete data	57%	[7,8]
Sequential minimal optimization (SMO)	SMO works on decomposing multiple variables into sub-	Qp can be solved analytically.	72.39%	[9,10]

Received 25 April 2021; Accepted 08 May 2021.

	problems.			
Bayesian network	It is a probabilistic graph model. They are used for prediction purposes.	BN is used for the analysis of data. Suitable for incomplete and small data sets	88.68%	[2, 3,4]
Neural Networks (NN)	NN deals with clustering of several input data and provide the classified output	Fault bearing capability (+) Can handle data with noise	89%	[16,17,18,19,20]
K Nearest Neighbor (KNN)	KNN is a non-parametric and lazy learning algorithm. k is the number of nearest neighbors and is the core deciding factor.	Easy and simple implementation (+) Does not assume data	93%	[21,22]
Support Vector Machine (SVM)	SVM works with the principle of fixed vector and mode identification.	Require less parameters to consider Avoids over fitting issue	97%	[5,6]
Bat Algorithm	Bat algorithm deals with the echolocation characteristics. It deals with frequency, the velocity of moving body	Frequency tuning is efficient to solve problems BA has the capability of automatically zooming into a region where promising solutions have been found	94%	[13,14,15]
Backpropagation	Bp assigns weight to each node and fed backward to derive a function	BP is fast, simple, easy to implement.	89.9%	[11,12]

Case study 1 for backpropagation network classifier

Title: Age group classification from the facial image.

Face aging has been a vital area of research for the past two decades. As age increases, there are some visible changes in the face, making age classification easier. Based on facial growth, we can classify the human age into various kinds. The facial image is pre-processed, and then the face image is extracted using the wavelet transformation. The distance between each of the features is evaluated using the Euclidean distance, and output is arrived using it. The neural network is trained using PCA. The human age is classified into three categories as a child (0-15 years), adult (15- 30 years), and senior adult (30 years and above).

Here classification is done using a backpropagation classifier. This project presented a theory and practical computations for visual age classification from facial images. The theory has only been implemented to classify input image into one of the three age groups, i.e., babies, young adults, and senior adults. The computation is based on facial features and distance measures. In the implementation, primary features of the face are found first, followed by secondary feature analysis. The primary features are the eyes, nose, mouth, chin, virtual-top of the head, and the face's sides. From these features, ratios that distinguish babies from young adults and seniors are computed.

Two backpropagation networks are constructed in the age classification phase. The first one is used to classify whether a facial image is a baby. The output is the value between zero and one. If the output is larger than 0.5, then the image is classified as a baby. If an image is not classified as a baby, the second neural network is activated to determine whether it is a young adult, middle-aged adult, or an old adult. The network has three layers as a young, middle-aged, old adult. The second network's input vector consists of nine wrinkle features obtained from three neurons in the output layer: the senior adults, the middle-aged adults, and the young adults. The output is all between 0 and 1. The highest output value of the neurons decides to which age group the image belongs.

Case study 2 for SVM Classifier

Title: Fake biometric detection using the features of image quality

The challenge was to identify the person based on their behavioral and physiological characteristic such as fingerprint, face, iris, voice, etc. In this project, 25 image quality features are extracted from a single image, and this

Received 25 April 2021; Accepted 08 May 2021.

information is used to discriminate the fake traits. This approach represents a lesser degree of complexity, and hence it is used in real-time applications. The classifier used here is the SVM classifier.

In recent years, the support vector machine has been advocated for its structure risk minimization leading to tolerance margins of decision boundaries. Structures and performances of these pattern classifiers depend on the feature dimension and training data size. Support Vector Machines (SVMs) serve as useful tools in classifying data by obtaining a hyperplane that separates the positive and negative examples by the maximum margin.

In this project, the features extracted from the image are stored at the back end. Hence these features are used to classify the fake biometrics by SVM classifier. The SVM classifier is taken for both training and testing phases. The training phase is used here to store the trained image feature value in a two-dimensional array at the back end, and the testing phases are to compare the feature values with the stored training values. Hence if the feature values are found to be the same, then the image is found to be real; otherwise, it is found to be fake.

Recent advancement in gait recognition

This section consists of related works and technologies in gait recognition. Latent Dirichlet Allocation (LDA) was later considered a topic model to evaluate human gait identification and human action recognition [23]. Additionally, the emphasis was specified to study gait silhouettes from a three-dimensional perspective. 3D analog of GEI was used to progress appearance-based gait identification techniques. The resulting volumes were named Gait Energy Volumes (GEV) and were employed on the CMU MoBo database [24][25]. [26] proposes an attributed discovery model in a max-margin framework to identify a person-centered gait while walking with multiple people. First, human graphlets are integrated into a tracking-by-detection method to obtain a person's complete silhouette. Researchers recommended using dynamic electromyogram (EMG) signals for the said purpose. Several body parts whose motion could deliver some identity information during gait were noted to analyze gait as a biometric [27].

Subsequently, efforts were made to study the gait signatures using a wireless sensor-based approach. Several body parts whose motion could provide some identity information during gait were recorded to analyze gait as a biometric [27]. A single uncalibrated camera was used to develop the positions of the joints for any walking subject. Gait signature was constructed through extraction for joint positions of walking people. Some researchers also chose the width of the silhouette's outer contour as a basic image feature because of its structure and dynamic aspects.

The use of a generic width vector was suggested to derive direct and Eigen based gait features. Template matching of body silhouettes to perform subject classification through nearest-neighbor matching among correlation scores was examined. Venkat et al. [28] also divided the averaged silhouette into several overlapped parts, including upper, middle, and lower parts as well as the left and right parts. They trained a Bayesian network to evaluate these parts' impact on identification and achieved good accuracy with backpack pedestrians.

Gu et al. [29] proposed a method to extract key points automatically and pose parameters from the sequence of label-free three-dimensional volume data and then estimated the multiple configurations (a combination of joints) and movement features (position, orientation, and height of the body) [30][31].

4. CONCLUSION

Gait recognition is to be a valuable asset in the biometric field. In table 1, the accuracy percentage of the various classification algorithms are measured. This paper reviews the way each classifier being used in gait recognition. The challenges include moving object segmentation. The background subtraction technology is used in various outdoor conditions such as light and shadow, so an adaptable background environment is required. Priority will be given to each feature to check the performance of the algorithm during run time. The mean absolute error is calculated to represent the average error. The features derived from the given image are essential for classification efficiency. The performance of SVM and KNN is found to be quite useful. KNN is the dominating classifier because of its

Received 25 April 2021; Accepted 08 May 2021.

simplicity. The feature selection is the priority task for the excellent performance of the classifier. The NN and Bayesian network performance are slightly different by percentage. NN algorithm can handle the data with noise.

At the same time, SVM requires fewer parameters to avoid the fitting issue. SMO classifier depends on only small datasets and provides good performance. Simultaneously, the system gives bad performance while using naïve Bayes since it is not debatable as naïve Bayes uses a different set of algorithms with a vast dataset that results in bad performance. We have discussed the different types of classification techniques used in gait recognition, and it is concluded that KNN is the adaptive classifier. The co-variant condition affects the performance in the gait recognition. The future direction deals with 3D modeling, and multiple cameras employing is accurate to calculate the result. The percentage of classification may change with the number of recognized people. Further research is in progress in the direction of a set of heterogeneous classifiers.

REFERENCES

- [1] Zeng W and Wang C (2016), "View-invariant gait recognition via deterministic learning", *Neurocomputing*, Vol.175, pp.324–335.
- [2] Judea pearl (1985), "Bayesian networks: A model of self activated memory for evidential reasoning via national science foundation", grant #DSR 83-13875
- [3] Cayci A, Eibe S, Menasalvas E, and Saygin Y (2010), "Bayesian networks to predict data mining algorithm behavior in ubiquitous computing environments via In Analysis of Social Media and Ubiquitous Data", Springer, Berlin, Heidelberg, pp. 119-141.
- [4] Procházka, A, Vyšata, O, Vališ, M, Tupa, O, Schätz, M, Marík, V (2015), "Bayesian classification and analysis of gait disorders using image and depth sensors of Microsoft Kinect. Digit via Signal Process. 47, 169–177.
- [5] C. Cortes and V. N. Vapnik, "Support vector networks. Machine Learning", vol. 20, no. 3, pp. 273-297, 1995.
- [6] Gao Fa-rong, Wang Jia-jia, Xi Xu-gang, She Qing-shan Luo Zhi-zeng (2015), "Gait Recognition for Lower Extremity Electromyographic Signals Based on PSO-SVM Method via Journal of Electronics & Information Technology", vol. 37(5), pp.1154-1159.
- [7] Parsania, V., Bhalodiya, N. and Jani, N.N (2014), "Applying Naïve bayes, BayesNet, PART, JRip and OneR Algorithms on Hypothyroid Database for Comparative Analysis via *International Journal of Darshan Institute on Engineering Research & Emerging Technologies*", vol. 3, no. 1.
- [8] Patil, T.R. and Sherekar, S.S (2013), "Performance analysis of Naive Bayes and J48 classification algorithm for data classification via International journal of computer science and applications", vol. 6, no. 2, pp. 256-261.
- [9] Platt, J (1998), "Sequential minimal optimization: A fast algorithm for training support vector machines."
- [10] G. Tsoumakas and I. Vlahavas. Random k-labelsets (2007), "An ensemble method for multilabel classification via In Machine Learning: ECML, pages 406–417. Springer.
- [11] Robert Hecht-Nielsen (1989) "Theory of the Backpropagation Neural Network" HNC, Inc. 5501 Oberlin Drive, San Diego, CA 92121, 619-546-8877
- [12] G. Venkata Narasimhulu, Dr. S. A. K. Jilani (2012) "Back Propagation Neural Network based Gait Recognition via International Journal of Computer Science and Information Technologies" Vol. 3 (5), 2012, 5025 – 5030.
- [13] Yang, X-S (2010). "A new metaheuristic bat-inspired algorithm. in Nature inspired cooperative strategies for optimization (NICSO 2010)". Springer. 65-74.
- [14] Swathi J.N (2016), "A Survey on Nature Inspired Metaheuristic Techniques for Training Feedforward Neural Networks via International Journal of Pharmacy & Technology", vol. 8, no.3, pp. 4567-4590.
- [15] M. Saad, M. Nor, F. Bustami, R. Ngadiran (2007) "Classification of heart abnormalities using artificial neural network via Journal of Applied Sciences", vol. 7, issue 7, pp. 820-825, 2007
- [16] John Mark Bishop (2015) "History and philosophy of neural networks (2015) John Mark Bishop" :<https://www.researchgate.net/publication/271841595>
- [17] B. Jayanta, B. Debnath, K. Tai-hoon (2010), "Use of artificial neural network in pattern recognition via International Journal of Software Engineering and Its Applications", vol. 4, no.2, pp. 23-34,.
- [18] R. Gross and J. Shi (2011), "The CMU Motion of Body (MoBo) Database, Tech. via Robotics Institute, Carnegie Mellon University" report CMU-RI-TR-01-18.
- [19] M. Saad, M. Nor, F. Bustami, R. Ngadiran (2007), "Classification of heart abnormalities using artificial neural network via Journal of Applied Sciences", vol. 7, issue 7, pp. 820-825.

- [20] R. David, L. Sovan, D. Ioannis, J. Jean, L. Jacques, A. Stephane (1997), "Artificial neural networks as a classification method in the behavioural sciences via Behavioural Processes", vol 40, issue 1, pp. 35-43.
- [21] E. Fix and J. Hodges (1951), "Discriminatory analysis, nonparametric discrimination: Consistency properties via Technical Report 4, USAF School of Aviation Medicine", Randolph Field, pp. 261-279, Texas, USA, Tech. Rep., 1951. [2] T. Cover and P. Hart, "Nearest
- [22] W. Aiguo, A. Ning, D. Chen, L. Li and G. Alterovitz (2014), "Accelerating incremental wrapper based gene selection with K-Nearest-Neighbor via IEEE International Conference on Bioinformatics and Biomedicine" pp. 21 23.
- [23] N.A. Deepak, U.N. Sinha (2016), "Analysis of human gait for person identification and human action recognition via Commun. Appl. Electron". 4 (4) 14, [https:// doi.org/10.5120/cae2016652080](https://doi.org/10.5120/cae2016652080).
- [24] S. Sivapalan, D. Chen, S. Denman, S. Sridharan, C. Fookes (2011), "Gait energy volumes and frontal gait recognition using depth images via International Joint Conference on Biometrics (IJCB)", IEEE, p. 16, <https://doi.org/10.1109/IJCB.2011.6117504>
- [25] R. Gross and J. Shi (2011), "The CMU Motion of Body (MoBo) Database, Tech. via Robotics Institute, Carnegie Mellon University" report CMU-RI-TR-01-18.
- [26] Xin Chen, Jian Weng, Lu. Wei, Xu. Jiaming, "Multi-gait recognition based on attributediscovery via IEEE Trans". PatternAnal.Mach. Intell. 40 (7) (2018)16971710.
- [27] D. Gafurov, E. Sneekenes (2009), "Gait recognition using wearable motion recording rs, Eurasip J via Adv. Signal Process", <https://doi.org/10.1155/2009/415817>.
- [28] Venkat, I., DeWilde, P (2011), "Robust gait recognition by learning and exploiting sub-gait characteristics via Int. J. Comput. Vis" 91(1), 7–23.
- [29] Gu, J., Ding, X., Wang, S., Wu, Y (2010) "Action and gait recognition from recovered 3-d human joints via IEEE Trans. Syst., Man", Cybern. B 40(4), 1021–1033.
- [30] Ying Zhang, Lin Wang, and Qinghong Wu, Chunshu Wu, "Review of Gait Recognition Methods,"
- [31] Venkat, I., DeWilde, P (2011), "Robust gait recognition by learning and exploiting sub-gaitcharacteristics via Int. J. Comput. Vis" 91(1), 7–23.