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Multi Task Learning System for Face and Gait Recognition and Comparison of Different Algorithms on These Recognitions

Komal Vyas, Shahana Qureshi
Raipur Institute of Technology, Raipur, India
Email address: vyaskomal92@gmail.com

Abstract— *In many fields one needs to build predictive models for a set of related machine learning tasks, such as information retrieval, computer vision and biomedical informatics. Traditionally these tasks are treated independently and the inference is done separately for each task, which ignores important connections among the tasks. Multi-task learning aims at simultaneously building models for all tasks in order to improve the generalization performance, leveraging inherent relatedness of these tasks. As in our project we are dealing with the Face recognition and the Gait recognition combine.*

Face recognition: Face recognition is a task so common to humans, that the individual does not even notice the extensive number of times it is performed every day. y. Many face analysis and face modeling techniques have progressed significantly in the last decade. However, the reliability of face recognition schemes still poses a great challenge to the scientific community.

Gait recognition: Gait recognition is the process where the features of human motion are automatically obtained/extracted and later these features enable us to authenticate the identity of the person in motion. gait recognition technique also involves 2 stages: Information is derived from human locomotion in the first stage i.e. feature extraction stage and in the next stage, i.e. the recognition stage, a standard similarity computation technique is used to obtain results for being a match or a mismatch. A unique advantage of gait as a biometric is that it offers potential for recognition at a distance or at low-resolution or when other biometrics might not be perceivable.

Combining these two recognitions is known as multi task learning.

Keywords— *Face Recognition, Gait Recognition, Nearest Neighbour, MultiTask Learning, PCA, LDA.*

I. INTRODUCTION

Face recognition: The most intuitive way to carry out face recognition is to look at the major features of the face and compare these to the same features on other faces. Some of the earliest studies on face recognition were done by Darwin and Galton. Darwin's work includes analysis of the different facial expressions due to different emotional states, where as Galton studied facial profiles. However, the first real attempts to develop semi-automated facial recognition systems began in the late 1960's and early 1970's, and were based on geometrical information. Here, landmarks were placed on photographs locating the major facial features, such as eyes, ears, noses, and mouth corners. In summary, most of the developed techniques during the first stages of facial recognition focused on the automatic detection of individual facial features. The greatest advantages of these geometrical feature-based methods are the insensitivity to illumination and the intuitive understanding of the extracted features. However, even today facial feature detection and measurement techniques are not reliable enough for the geometric feature-based recognition of a face and geometric properties alone are inadequate for face recognition.

PCA Algorithm

One of the simplest and most effective PCA approaches used in face recognition systems is the so-called eigenface approach. This approach transforms faces into a small set of essential characteristics, eigenfaces, which are the main components of the initial set of learning images (training set). Recognition is done by projecting a new image in the eigenface subspace, after which the person is classified by comparing its position in eigenface space with the position of known individuals [3]. The advantage of this approach over other face recognition systems is in its simplicity, speed and insensitivity to small or gradual changes on the face. The problem is limited to files that can be used to recognize the face. Namely, the images must be vertical frontal views of human faces. The whole recognition process involves two steps:

A. Initialization process

B. Recognition process The Initialization process involves the following operations:

i. Acquire the initial set of face images called as training set.

ii. Calculate the Eigenfaces from the training set, keeping only the highest eigenvalues. These M images define the face space. As new faces are experienced, the eigenfaces can be updated or recalculated.

iii. Calculate distribution in this M-dimensional space for each known person by projecting his or her face images onto this face-space. These operations can be performed from time to time whenever there is a free excess operational capacity. This data can be cached which can be used in the further steps eliminating the overhead of re-initializing, decreasing execution time thereby increasing the performance of the entire system . Having initialized the system, the next process involves the steps:

- Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the Eigenfaces.
- Determine if the image is a face at all (known or unknown) by checking to see if the image is sufficiently close to a free space.

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- If it is a face, then classify the weight pattern as either a known person or as unknown. iv. Update the eigenfaces or weights as either a known or unknown, if the same unknown person face is seen several times then calculate the characteristic weight Face Recognition Using Principal Component Analysis pattern and incorporate into known faces.

The last step is not usually a requirement of every system and hence the steps are left optional and can be implemented as when the there is a requirement.

Nearest Neighbour

k-nearest neighbor algorithm is a method for classifying objects based on closest training examples in the feature space. k-nearest neighbor algorithm is among the simplest of all machine learning algorithms. Training process for this algorithm only consists of storing feature vectors and labels of the training images. In the classification process, the unlabelled query point is simply assigned to the label of its k nearest neighbors. Typically the object is classified based on the labels of its k nearest neighbors by majority vote. If k=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, k must be an odd integer. However, there can still be ties when k is an odd integer when performing multiclass classification. After we convert each image to a vector of fixed-length with real numbers, we used the most common distance function for KNN which is Euclidean distance:

Gait recognition: As a young branch of biometrics, human gait has its own advantages such as data acquisition from distance, non-invasive, hard to conceal. It has great potential for security-oriented applications like the identification of individuals, video surveillance etc. The techniques used for gait recognition can be divided into two categories: model-based methods and appearance-based methods. The former usually extract the motion features through tracking the body parts and measuring the parameters using articulated models. The appearance (holistic) based methods that address the gait recognition problem using only sequences of binary silhouettes are of much interest since other information like color or gray scale may not be available in practical cases.

Background removal: In image processing there is a step involved known as preprocessing of the image where the primary step is segmentation. This refers to the gait where the background is separated from the foreground to isolate the foreground. Within the gait recognition system identical principle is used. From the video frame work the moving objects square measure separated from the writing paper one can thought of it as the background. The background removal techniques:

Non Recursive technique: A window approach for estimating the background is employed. This method doesn't rely upon the History.

Recursive technique: On the opposite hand will be the opposite; it doesn't maintain any buffer for background estimation. A mathematician model is employed to recursively update one background model supported every input frame. Post the background subtraction some noises perhaps present, to alleviate the noise a filter like a Median filter. Recursive techniques need less storage resources.

Feature extraction: Feature extraction plays a very important role within the gait recognition system. Once the background is deducted from the image, every image sequence is reborn into a brief sequence of distance signals. The feature of a picture is painted employing a vector. And Silhouette is extracted; it is outlined as region of pixels of walking person. There square measure are completely different silhouette stances throughout gait cycle, they embody midstance, double support. Mostly used feature extraction approaches are square measure particularly model based mostly approach and therefore the non-modeled/holistic approach.

Model based approach: Using this approach it need a prime quality video sequences because it is scaled and consider invariant. The parameters used as options within the approach are square measure the peak, the gap between the pelvis and feet and therefore the distance between the feet. The silhouette is split into some regions. These regions square measure feature vectors that embody averages of the centre of mass, the ratio and orientation of the foremost axis of the conic section.

Holistic based approach: Holistic approaches target the form of the silhouette as the motion of the full body as compared to model based that mostly that target a selected a part of the body. These approaches don't seem to be dependent to quality of the video frame. What is more they provide less machine necessities and complexities. But they're sometimes not as sturdy as compared to model based mostly approaches. In holistic approaches the contour of the silhouette is thought to be a crucial issue of the tactic. It are often reworked to extract Fourier descriptors. For top quality silhouette the outer contour of silhouette is regarded the vital feature. On the opposite hand binaries silhouettes are used for quality silhouette because of the vital feature.

Feature Dimensionality reduction: After the feature extraction method, the options are extracted however they're at high dimensions which require to be reduced to decrease the failure of typical classification algorithms. So the importance of the feature reduction algorithmic rule, that solely extracts the helpful options for classification

PCA Algorithm

PCA may be a methodology that's wont to change information structure and still retain the initial data. It's a way accustomed analyze information statically to search out the principal part within which information is probably going to vary. This methodology identifies patterns in knowledge light their variations variations. PCA is employed in compression and pattern recognition rule. in a very gait recognition system is employed as a classical linear methodology to cut back knowledge spatiality whereas accounting for as knowledge originality as potential.

LDA

LDA is an approach that is used in feature extraction specifically in the process of reducing the dimensionality of data.it performs training and projection on original gait feature.it employs the use of PCA together with the LDA

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algorithm to reduce the dimensionality of data while preserving as much originality as possible.

Challenges in Gait Recognition

External factors: These are factors that surround the individual being known like lighting conditions, viewing angle, weather, walking surface, clothes, shoe types, baggage being carried and soon.

Internal factors: Internal factors are those who have an effect on the user's body internally like aging, sickness, drunkenness, weight gain or loss, pregnancy, accidents soon.

Multitask System

Multi-task learning (MTL) is a subfield of machine learning in which multiple learning tasks are solved at the same time, while exploiting commonalities and differences across tasks. This can result in improved learning efficiency and prediction accuracy for the task-specific models, when compared to training the models separately. Multitask Learning is an approach to inductive transfer that improves generalization by using the domain information contained in the training signals of related tasks as an inductive bias. It does this by learning tasks in parallel while using a shared representation; what is learned for each task can help other tasks be learned better. Multi-task learning works because regularization induced by requiring an algorithm to perform well on a related task can be superior to regularization that prevents overfitting by penalizing all complexity uniformly. One situation where MTL may be particularly helpful is if the tasks share significant commonalities and are generally slightly under sampled.

Fig. 1. Multi task Learning (Face + gait).

Algorithm for Multitask Learning

- *Neural network :*

Richard Caruana et al. introduced a number of multi-target (multi-task) neural network approaches. Caruana (1993) presented the first MT neural network. They argue that generalization is improved by leveraging the domain-specific information in training-signals of related tasks and coined the term multitask inductive transfer. From the main task point of view, other tasks work as bias. Neural network uses a target specifies weights at the outpur layers and shared hidden layers for all tasks. The interpretation of hidden layer is done as the feature selection. Thus, the hidden layer share all the common tasks. s. This may lead to improved performance as the learner can use the information available for all targets, enabling targets with limited available data to benefit from the data available for other related targets. This approach creates a representation bias toward the intersection of what would be learned by the individual tasks.

Silver and Mercer (1996) introduces a method for the parallel transfer of task knowledge using dynamic learning rates. The MTL algorithm introduced which uses a higher learning speed for targets. It is based on weight space distance.

- *Multi target decision process :*

Most of the multi target decision trees assume the data from the single target, which may be a classification or regression. Blockeel, De Raedt, and Ramon (1998) argued that decision tree learning can easily be extended towards the case of multi-target prediction, where by extending the entropy class towards multi task learning. They define the variance of a set as the mean squared distance between any element of a set and a centroid of the set. It could be Eucledean distance in space. To give the accurate predictions for multiple target variables, a decision tree is build.

- *Kernel method*

A number of kernel methods has been proposed, mostly adaptations of Support Vector Machines (SVM). Evgeniou and Pontil (2004) proposed Regularized MTL. The kernel method algorithm is a straightforward method and is equal to single task learning or we can say it is better than the single task. But its performance works well for first 30 targets and than gradually decreases after 100 targets. Trafalis and Oladunni (2005) proposes an alternative MTL-SVM algorithm. The rationale behind its performance increase, with relation to STL, is based on the assumption that the error terms, i.e. noise, for each target are correlated and that learning these targets together tends to cancel out noise

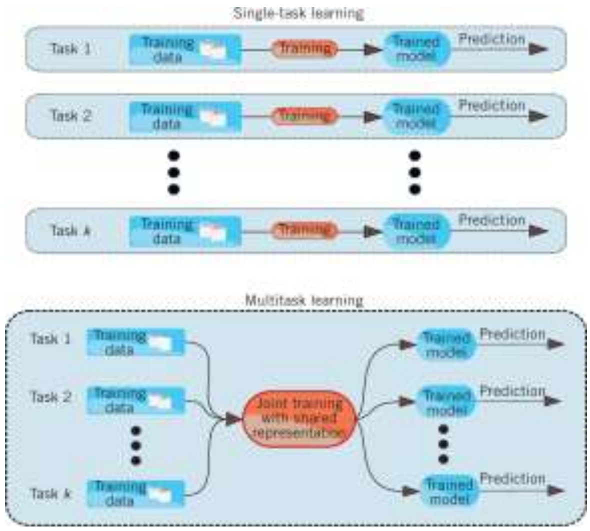

Fig. 2. Comparison between single and multitask learning.

- *Nearest neighbour algorithm*

Nearest Neighbor methods can be adapted to MTL by using a weighted distance measure with weights chosen to

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minimize the error for all targets in the training set. Thrun and O'Sullivan (1996) performed a number of experiments around clustering tasks which were then predicted with such a Nearest Neighbor method for each cluster.

II. Literature Review

This chapter provides a view of various papers. There are many papers published and researched on different fields like Face, Gait and Multitask Learning based on machine learnings. For decades, face recognition has been a major problem and many implementations and researches are done regarding this.

"Faizan Ahmad, Aaima Najam, Zeeshan Ahmad", Title "Image based Face detection and recognition State – of – the - art".

This paper showed various face detection and recognition methods , provide solution for image based face recognition , providing solution with higher accuracy , better response time solution are proposed which are tested on various databases , in term of pose, emotion , race and light. Provide Adaboost classifier with Haar and Local Binary Pattern of SVM classifier used with Histogram of Oriented Gradients.

"M.Pushpa Rani and G Arunugam", Title" An Efficient Gait Recognition System for Human Identification using Modified ICA"

This paper propose an efficient self-similarity based gait recognition system for human identification using MICA. i.e Modified independent component Analysis. Here background modelling is done followed by frame segmentation using background substraction algorithm. MICA based on eigenspace transformation is than trained using the datasets. Thus this recognizes the gait feature and thereby humans based on self-similarity measures.

"Pranjit Das and Sarat Saharia" Title" Human Gait Recognition based on PCA"

Human gait is used as Principal component Analysis, identifying feature to generate unique sequence for each individual. Gait feature here are extracted such as centriod, aspect ratio, orientation, height and width. Than PCA is employed over the generated feature vector and produce principal component which are used as gait sequence. The generated gait sequence and individual are than recognized using minimum distance classifier. In this paper, about 93% classification rate is achieved.

"Gloria Zen, Enver sangineto, Nicu Sobe" Title" Unsupervised Domain Adaptation for personalized Facial Emotion Recognition"

This paper presents personalization approach in which only unlabelled target specific data are required. Here, first a regeression framework proposed to learn the relation between user specific sample distribution and parameters of there classifier. After this a target classifier can be constructed using only the new user's sample distribution to transfer personalized parameter. This paper introduces a new method to represent source sample distribution based on using o only support vectors of source classifier.

"Zhanxiong wang, Kekehe, Rui feng, Yu-Gong Jiang" Title "Multi task deep neural network for joint recognition and facial attribute Prediction."

In this paper, for the first time we advocate a multi task deep neural network for jointly learning face recognition and facial attribute prediction task. This multitask face recognition network of both full Model and Fast model. Here they used the deep learning methods. As most datasets don't have facial attribute tagged, the primary task is to come up with attribute labels. second step we tend to take as input of our network. here used the datasets of CelebA to train the facial attributes. We tend to assume that the chosen facial ought to be consistent. In this paper, our fast-Model is very efficient and can beat the small protocols. It is good for in terms of running cost and performance.

"Junho Yim Heechul, jung Byungin Yoo, Changkyu choi, Dusik Park" Title "Rotating your face using Multitask deep neural network"

It proposed a new deep architecture based on novel type of multitask learning which can achieve superior performance in rotating face image from an arbitrary pose and illumination image. This type of multi task model improves identity preservation over the single task model. By using all synthesized controlled pose image for pose illumination-invariant feature. The input image under an arbitrary pose and illumination-invariant is transformed into another pose image. The remote code represent the target pose code corresponding to output image.

"Henry A Rowley, Shumeet Baluja , Takeo" Title "A neural network based face detection"

This paper examines small windows of an image and decide whether each window contains a face. The system work over the multiple network to improve performance over a single network. We use bootstrap algorithm for training the network which adds false detection into training set, eliminating the difficult task of manually selecting the non-face training examples. This system has better performance in terms of detection and false positive rates.

"Xi yin and Xiaoming liu" Title "Multi task convolution neural network for post invariant face recognition"

This paper proposes the multi task learning for face recognitions. It proposes a multi task convolution neural network where identify classification is the main task. And all other side tasks are pose, illumination, expression estimates etc. Secondly we develop a scheme to automatic assign the loss weight to each side task. Than a pose directed multi task CNN by grouping different pose to learn features.it is first work using all data in multi-PIE for face recognition. For different datasets, different results are generated.

III. Problem Identification

Through many years, Science have developed a lot in the field of image processing. Many Researches have developed over using many different algorithms and methodology and even they got a great success. But the actual problem arises when we have many different tasks to be performed simultaneously. For giving accurate results, it is necessary to have a good Learner which can work effectively for all the tasks.

In our project, we are even dealing with such a problem. As we are having two different recognitions i.e. gait and face recognition which have to be recognized simultaneously accurately and in less time. The CASIA datasets have been used for Gait and face recognition and Multi task learning will be applied for it. The actual problem is working with the two different datasets at the same time and also knowing which algorithm will fit into it and is best to apply.

So, Here we will study the problem that arise and also compare and analyze the different algorithms to have an idea of which algorithm fits the best for image (Face and Gait) recognitions.

IV. METHODOLOGY

In our project, we are dealing with the multi task learning using the two different tasks that work simultaneously i.e the Gait and face recognition. First the training data of face and gait datasets are labeled and given as input to the machine after they are converted into a feature matrix vector of same dimensions. and than for testing data of face and gait are given as input to the machine . The output came is the testing data in correspond to the labeled data.

This is the actual method involved in our project including the detection, extraction and recognition of data with more accuracy and in less time. Somewhere when these tasks are learned indivisially may not give that much accurate result but when learned and worked together in one platform may provide a better result which is more accurate, more fast, consumes less memory etc.

Flow diagram of Face Recognition Methodology

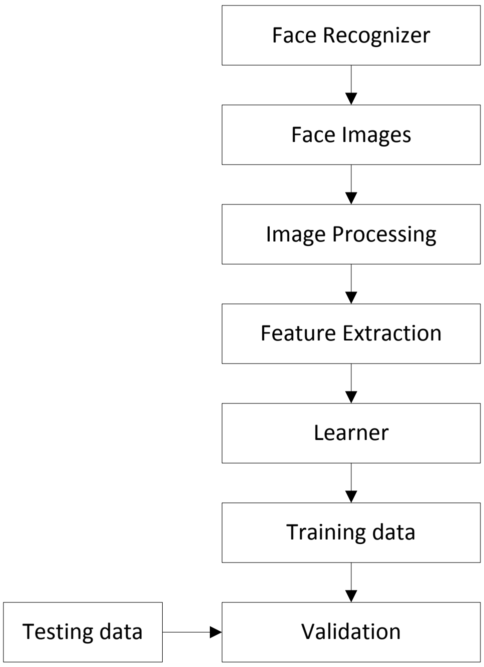

Fig. 3. Face recognition process.

Here we are providing the CASIA datasets for both gait and face recognition. And some data are provided for the training set and rest for the testing set. They work good for a no. of datasets of many instances. Also the different types of plotting are formed accordingly i.e. Scatter, Confusion, ROC matrix. here we are making a case study of the multi task learning and also we are comparing the above 3 matrixes for both the gait and face recognitions on how they work and fluctuates accordingly.

In our project, we are using the Linear programming. The algorithm we are using is PCA algorithm and classifier used is K.Nearest neighbour classification.

Face Recognizer

Here the software recognizes the datasets that have been given as an input. The task is to find the location and sizes of all the images that belong to a particular class. Focus on frontal face image and recognizes bit by bit.

4.1.2 Feature Extraction

Feature Extraction is generally known as dimensionality reduction. It starts from a set of initial data which is informative and non. Redundant. When an input data to an algorithm is too large to be processed and it might be redundant than it can be transformed into a reduced set of features (also named a feature vector. Determining a subset of the initial features is called *feature selection*. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved.

Classifier: Classification is actually a process in which all the individual items (objects/pixels/pattern) are grouped based on the similarity between the items and the description. It is used as the last stage in automated image analysis. Once a feature selection finds a proper representation, a classifier can be designed using a number of possible approaches The performance of classifier depends on the interrelationship between sample size, number of features and classifier complexity The choice of a classifier is a difficult problem!!! It is often based on which classifier(s) happen to be available or best known to the user. In our project we used the Nearest Neighbour Classifier. The k. nearest neighbour is a non. Parametric method used for classification and regression. *k*-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The *k*-NN algorithm is among the simplest of all machine learning algorithms. Assigns pattern to majority class among k nearest neighbour. The best choice of k depends on the data , as larger values reduces the noise effect on the classification.

Training Data

In machine learning study and construction of algorithm that can learn from or make predictions on data is a very common task. Data which is to be build the final model comes from multiple datasets. The model is first fit into the training dataset. The training datasets are used to train the algorithm.

The better the training data, better is our algorithm. The datasets are trained using the Supervised learning. There are no fix size upon which the training data should be choosen.

4.1.5 Testing Data

The Test dataset provides the gold standard used to evaluate the model. It is only used once a model is completely trained(using the train and validation sets).

4.1.6 Validation

The validation set is used to evaluate a given model, but this is for frequent evaluation. We as machine learning engineers use this data to fine-tune the model hyperparameters.

Many a times the validation set is used as the test set, but it is not good practice. The test set is generally well curated. It contains carefully sampled data that spans the various classes that the model would face, when used in the real world.

Fig. 4 Face image datasets.

Flow Diagram of Gait Recognition Methodology

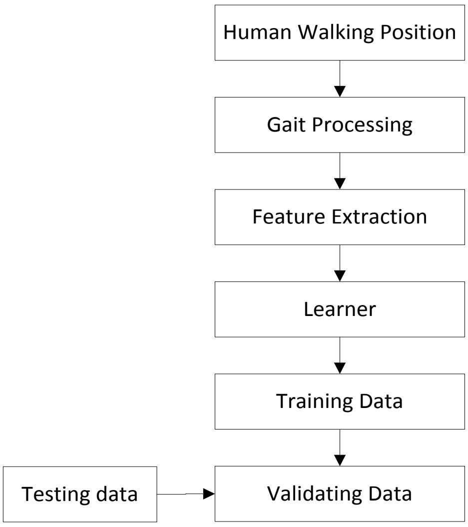

Fig. 5. Gait recognition process.

The same Process of Face recognition goes with the Gait recognition. The difference is the type of DataSets and the no. of datasets taken for testing and training.

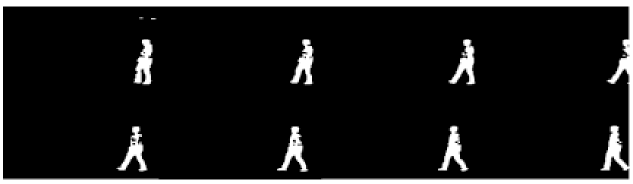

Fig. 6. CASIA dataset.

Multitask Learning

Process and Method

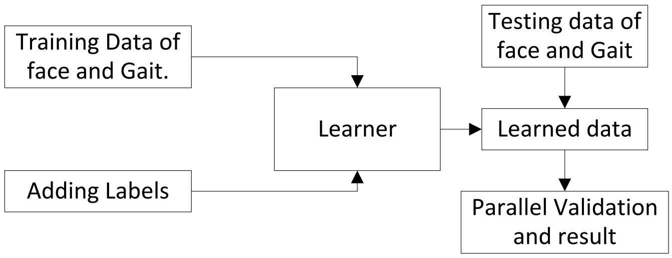

Fig. 7. Multi task learning.

The methodology we proposed in our project for the multi task learning is rather than doing the tasks indivisually, it will be helpful and will provide the accurate data and result if done by combining the two. The face and gait recognition as we have seen the indivisual method of its detection, extraction and recognition, now when they are given simultaneously to the learner, they function a quite different.

The training data sets along with the labels attached and by using the PCA algorithm they reduced the dimensionality of each and every image of both training and testing datasets and by adding the labels for indivisual objects the training datasets are embedded and given as input to the learner. The classifier learner will learn the data i.e. the images. On the other hand the testing data is given as input to the learner again to learn the data and the result that came out is the testing images with the respective labels. The result data that came out is different for both gait and face. Also the parallel validation is done while comparing the different algorithms for both the face and gait and providing with the 3 matrices.

Fig. 8. Multi task (As in project) diagram.

V. Result and Observation

In this table, we are testing the different no. of datasets and note the accuracy percent that occurs. It may fluctuate depending on the type of datasets and algorithm we use. For Ex In 1st row it depicts 4 as an object each consisting of 10 instances for training and 2 objects with 5 instances each for testing. This dataset is for Gait recognition accuracy similarly is for face recognition. Here we have trained and tested with different number of datasets.

When compared to other papers that are published , though our project is not up to the mark for giving the accuracy rate , but when they are trained and tested together , they retrieve the result in less time as compared to others. SVM algorithm is provided to be the best for the predictions of the accuracy.

In our project, we have used the PCA algorithm along with the Nearest neighbour.

TABLE 5.1 Accuracy table.

Gait Recognition			Image Recognition		
Training	**Testing**	**Accuracy %**	**Training**	**Testing**	**Accuracy %**
4 * 10	2 * 5	83.33%	3 * 7	3 * 3	55.55%
7 * 10	5 * 5	73.33%	5 * 7	5 * 3	73.20%
11 * 10	7 * 5	72.05%	7 * 7	7 * 3	82.66%
20 * 10	10 * 5	69.05%	15 * 7	15 * 3	79.57%
40 * 10	20 * 5	82.77%	30 * 7	30 * 3	70.07%
70 * 10	40 * 5	65.77%	40 * 7	35 * 3	75.09%
100 * 10	60 * 5	80.05%	60 * 7	40 * 3	62.22%

Comparison of Algorithms

MultiTask learning using Gait and Face recognition gives many significant results. In our project we compared the two Face and Gait with 5 different algorithms and plot those algorithms on two different types of matrices i.e. The ROC matrix and confusion matrix. Doing so we get the result that these algorithms better work for face recognition than with gait recognitions. But then also it fluctuates somewhere depending on the no. of training and testing datasets.

TABLE 5.2. Comparison of algorithm.

Algorithm	Face Recognition Accuracy	Gait Recognition Accuracy
Discriminent Analysis	90.5%	70.0%
Linear SVM (Support Vector Machine)	85.7%	62.5%
Fine KNN (K Nearest Neighbour)	85.7%	60%
SubSpace KNN classifier	85.7%	57.5%
SubSpace discriminent Classifier	100%	72.5%

Following we will be providing the matrices for all 5 different algorithms.

- *Discriminent Analysis*

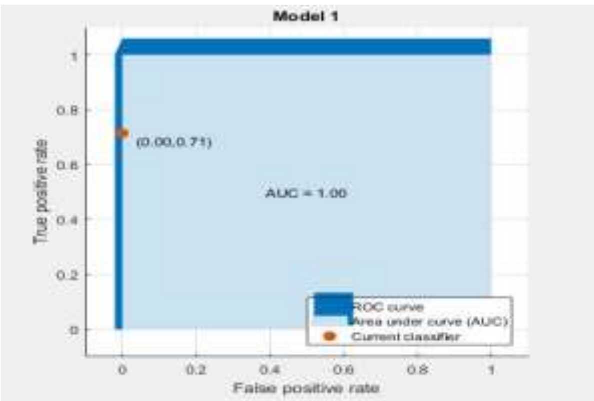

Fig. 5.1. Face ROC matrix.

- The face ROC Matrix for Discriminent Analysis describes that the area under curve = 1.which means that the classifier used is excellent or near to it.

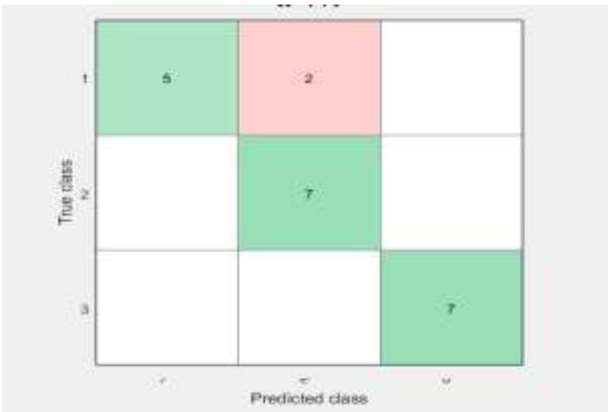

Fig. 5.2. Face confusion matrix.

- The face Confusion Matrix for discriminant Analysis describes that Total values taken = 7, Classes = 3.In 1st class , the classifier states that 5 instances belong to actual 1st class and rest 2 instances belong to 2nd class. In 2nd class , the classifier states that all 7 instances belong to 2nd class. In 3rd class, the classifier states that all 7 instances belong to 3rd class.

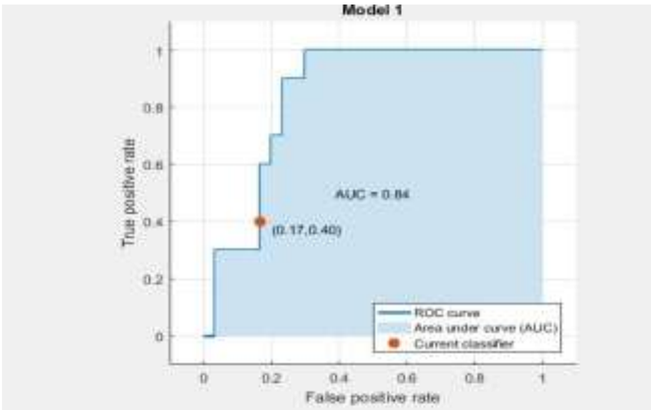

Fig. 5.3. Gait ROC.

- The Gait ROC for discriminent Analysis describes that the area under curve = 0.84.Which comes under the category of good classifier.

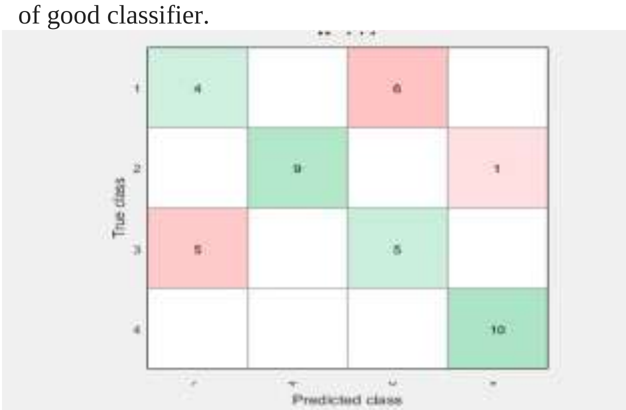

Fig. 5.4. Gait confusion matrix.

- In Gait Confusion matrix of Discriminent Analysis states that there are 4 classes each containing 10 instances. The matrix shows that in 1st class 4 instances are of class 1 but

6 instances belong to class 3.Similarly in 2nd class it shows that 9 instances belong to 2nd class but 1 instance belong to 4th class. In 3rd class it shows that 5 instances are true as they belong to same 3rd class but 5 instances belong to 1st class. In 4th class it shows that all the 10 instances correctly depicts that they belong to 4th class.

- *Linear SVM*

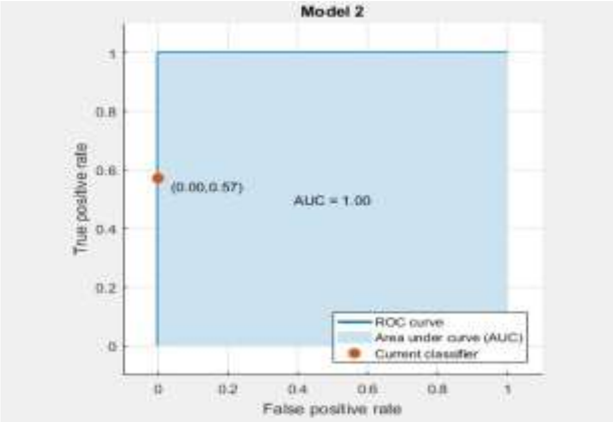

Fig. 5.5. Face ROC.

- In Face ROC of Linear SVM, the area under curve = 1. It shows that true positive rate is 0.57.Which can fall in category of good classifier.

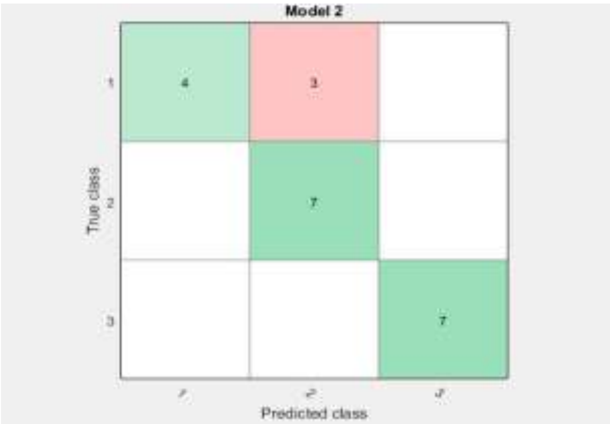

Fig. 5.6. Face confusion matrix.

- In Face Confusion Matrix of linear SVM, it states that there are 3 classes each consisting of 7 instances. Out of which , in 1st class the 4 instances correctly match to 1st class but the other 3 depicts class 2nd.Similarly in classes 2 and 3 shows that there all 7 instances belong to their same class

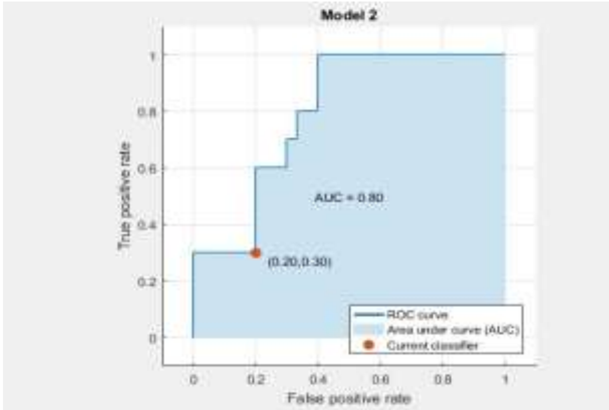

Fig. 5.7. Gait ROC.

- In Gait ROC of Linear SVM, shows that area under curve = 0.80.Which can be considered as a good classifier.

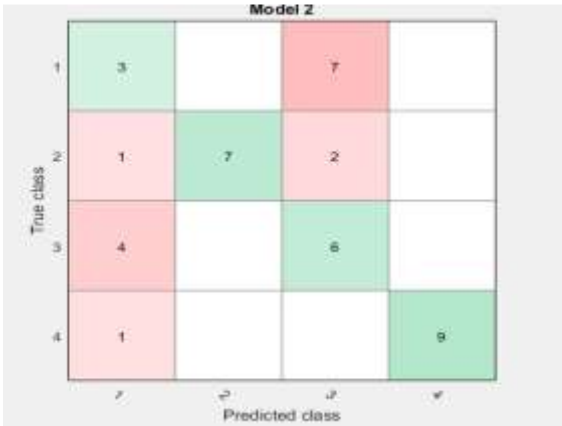

Fig. 5.8. Gait confusion matrix.

- In Gait Confusion Matrix of Linear SVM, it states that there are 4 classes with 10 instances in each. In 1st class, it shows the result that the 3 instances belong to the same class but 7 instances belong to class 3. In 2nd class, it shows that 7 instances belong to the same 2nd class but 1 instance is of 1st class and 2 instances are of 3rd class. Similarly for 3rd class it states that 6 instances correctly depicts that they belong to 3rd class but 4 instances show that they belong to 1st class. In 4th class, 9 instances belong to 4th class but 1 belong to 1st class.

- *Fine KNN*

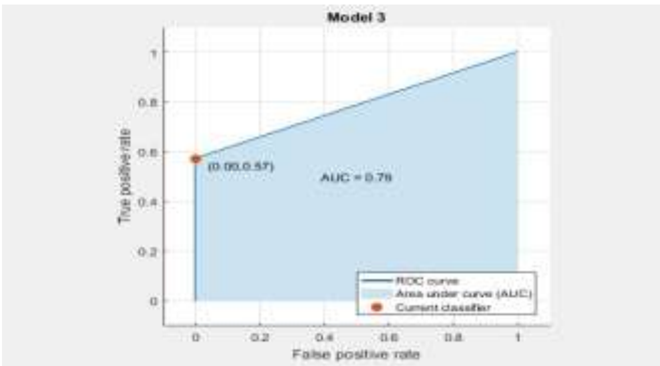

Fig. 5.9. Face ROC.

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- In Face ROC matrix of Fine KNN, shows that area under curve = 0.79. Though not too good but can be considered as a fair classifier.

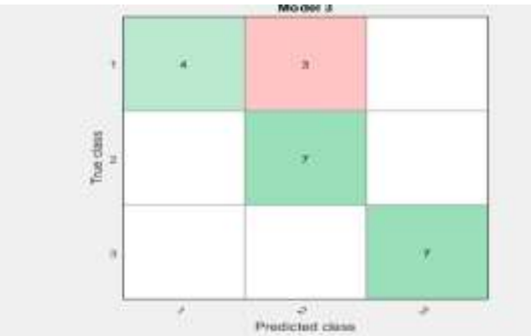

Fig. 5.10. Face confusion matrix.

- In Face Confusion Matrix of fine KNN algorithm , shows that for 3 classes with 7 instances each.in which ,1st class denotes that the 4 instances are correct but the rest 3 instances show that they belong to 2nd class. In 2nd class and 3rd class correctly depicts that all 7 instances belong to their corresponding class.

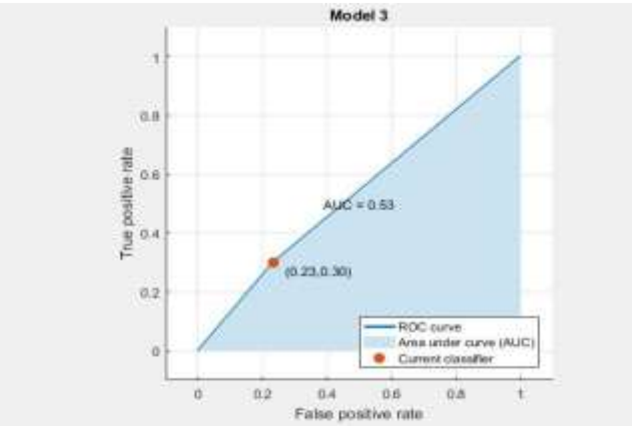

Fig. 5.11. Gait ROC.

- In Gait ROC matrix for fine KNN algorithm show the area under curve = 0.53. which is not good classifier classification.

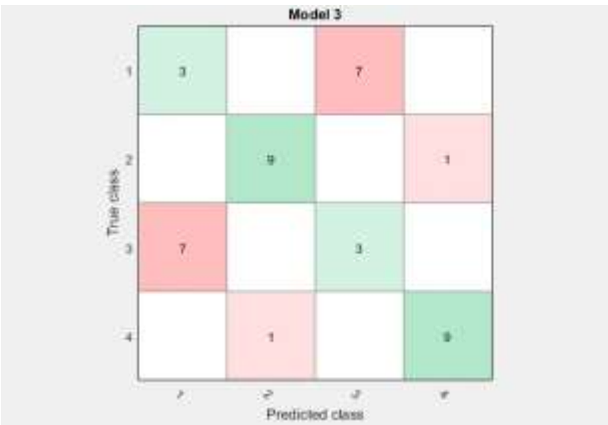

Fig. 5.12. Gait confusion matrix.

- In Gait Confusion matrix for Fine KNN algorithm, it shows the 4 classes with 10 instances each. Where in 1st class 3 instances are correct but 7 instances shows that they belong to class 3rd. In 2nd class, 9 instances are correct but 1 shows that it is of 4th class. In 3rd class, 3 are correct but 7 instances are of 1st class. In 4th class, 9 instances are correct but 1 belong to 2nd class.

- *Subspace KNN classifier*

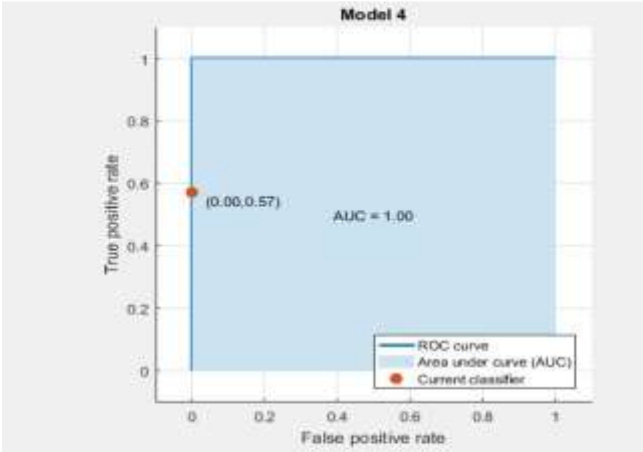

Fig. 5.13. Face ROC.

- In Face ROC of Subspace KNN classifier algorithm , it shows that area under curve = 1.,which can be classified as an excellent classifier.

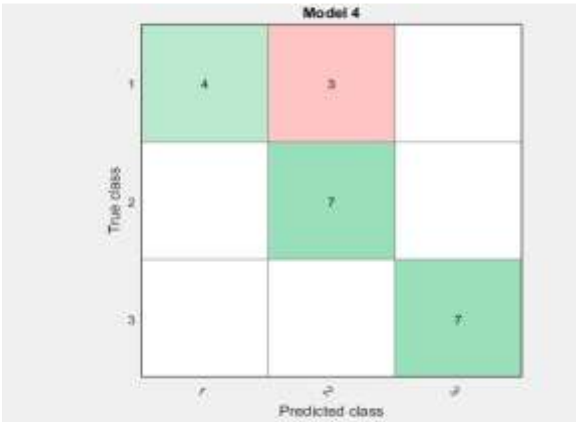

Fig. 5.14. Face confusion matrix.

- In face Confusion matrix of subspace KNN classifier , it consist of 3 classes with 7 instances each.In 1st class , 4 instances are same but 3 are different.Similarly 2nd and 3rd class all 7 instances are of respective classes

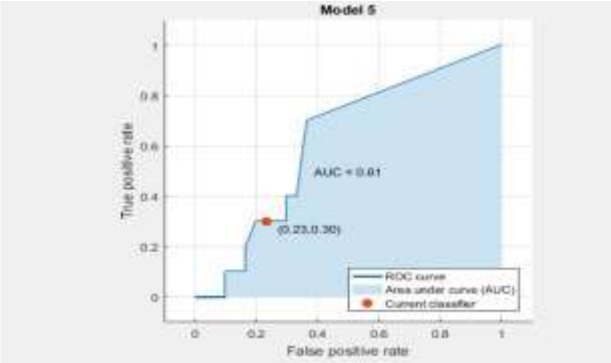

Fig. 5.15. Gait ROC.

- In Gait ROC of Subspace KNN classifier, area under curve = 0.61, which can be regarded as a good classifier.

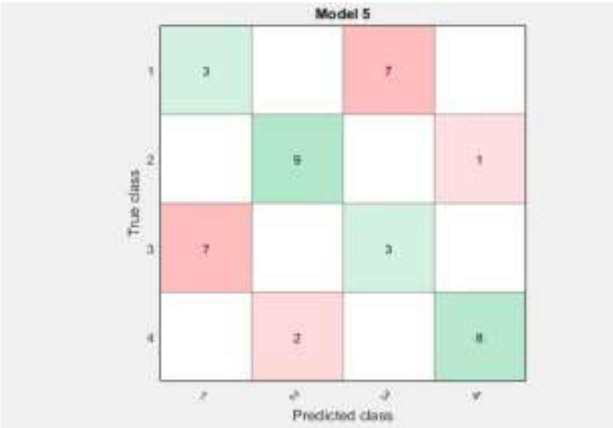

Fig. 5.16. Gait confusion matrix.

- In Gait Confusion matrix of Subspace KNN classifier, it states that for 4 class with 10 instances each , In 1st class 3 instances depicts correct but 7 instances belong to 3rd class. In 2nd class, 9 instances belong to exact 2nd class but 1 to 4th class. In 3rd class, it shows that 3 are correct but 7 instances show that they belong to 1st class. In 4th class, 8 instances are correct but 2 belong to 2nd class.

- *Subspace discriminent classifier*

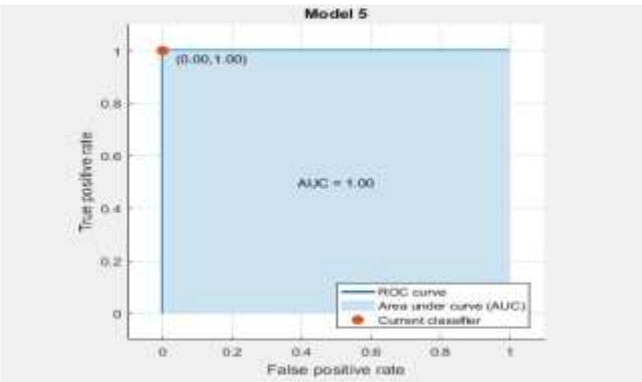

Fig. 5.17. Face ROC.

- In Face ROC of Subspace discriminent analysis algorithm, area under curve = 1. Which depicts that this classifier algorithm is excellent.

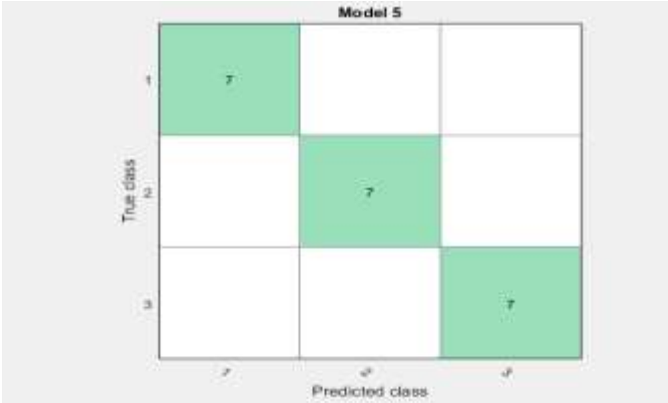

Fig. 5.18. Face confusion matrix.

- In Face confusion Matrix of subspace discriminent analysis algorithm, it shows that all the 7 instances belonging to 3 classes correctly describes the all their respective classes.

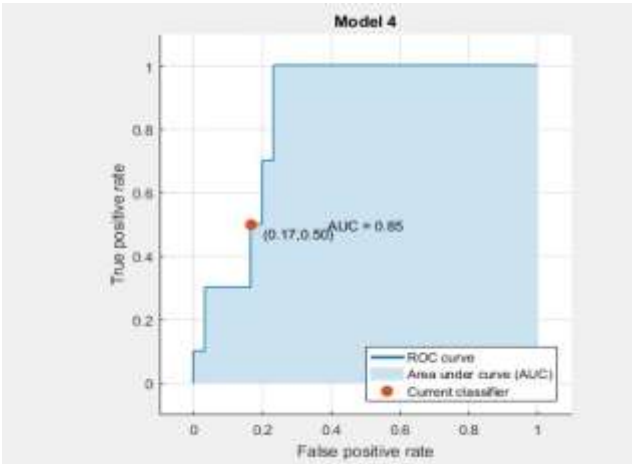

Fig. 5.19. Gait ROC.

- In Gait ROC of subspace discriminent analysis algorithm, the area under curve = 0.85.Which depicts it as a good classifier.

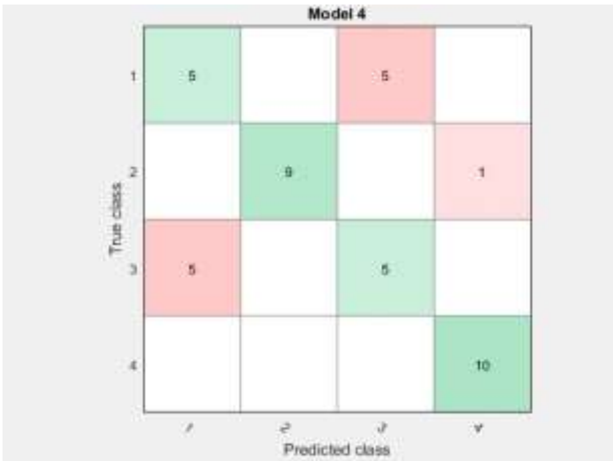

Fig. 5.20. Gait confusion matrix.

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- In Gait Confusion Matrix of Subspace Discriminent analysis algorithm, it shows that for 4 classes with each having 10 instances.in which the 4^{th} class correctly gets depicted by its instances that all 10 belong to 4^{th} class.

VI. Conclusion and Future Scope

In this work, we implemented the Multi task learning by applying two different tasks to make them solve at the same time. This can result in improved learning efficiency and in making predictions.by using the two recognitions i.e face and gait recognitions we came to a conclusion that the result that they provided when they are learned individually is quite different and requires more space, time to get execute. Even the accuracy of the result differs. The paper that we studied and the algorithm we performed gives the result that SVM algorithm outperforms the PCA and KNN algorithm. The change in this type of result is due to the fact that KNN algorithm cannot classify images and moving objects with that accuracy as it can be done using SVM algorithm.

But when working in multi task environment, this result is somewhat improved. Though not upto that level but a certain level.

In Gait algorithm when training sets are taken as 5 objects with 10 instances each 5 * 10 and testing sets are taken as 2 * 5 instances each, we find that the accuracy came is 81.5 %.

In face algorithm when training sets are taken as 3 * 7 and testing data are 3 * 3 instances, the accuracy found here is 55.5% only.

The performance of various classification methods still depend greatly on the general characteristics of the data to be classified. The exact relationship between the data to be classified and the performance of various classification methods still remains to be discovered. Thus far, there has been no classification method that works best on any given problem. There have been various problems to the current classification methods we use today. To determine the best classification method for a certain dataset we still use trial and error to find the best performance.

Future Work: Though the method proposed here is robust and trendy now a days as multi-tasking is a sub field of the machine learning. And also our result gives an average outpur of all datasets. The future scope is:

i.) In invention of different online games where two or more single tasks has to be combined properly.
ii.) In field of medicine and detection of many diseases in the body.
iii.) In schools while making the report cards and entering different features of student.

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