Transfer Learning and Deep Learning for Biometrics Recognition

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Abstract-
The important aspects for this era is Security. To achieve it, the most important and authenticated resource is Biometric based Systems. The objective of Biometrics recognition is to find and predict the new identifications. Biometric Recognition includes speech recognition, computer vision, Natural language processing etc. Biometric Feature have a unique identity in case, recognition comes into existence. Different types of Verification methods are acceptable .For deploying the method of recognition, more informations are collected. Among a number of methods, Deep Learning Technique overcomes the other situations. Basically Transfer Learning can be taken as a solution along with CNN (Convolutional Neural Network). The application of the method is showcasing the effectiveness and robustness.
Keyword- *Transfer Learning, Deep learning, Convolutional Neural Network*

Introduction To Transfer Learning

Artificial Intelligence and Machine Learning has an important area i.e Deep Learning. Usability of it lie with NLP (Natural Language Processing), Computer Vision etc. It also helps in the classification and recognition. Image Classification is one among them. it classifies any specific image to a set of possible availabilities. Image Recognition is implied as the software system ability of finding people, places, and objects. It can be best fitted with the examples taking two wheelers, three wheelers or four wheelers. A lot more work has been complied on image classification, image recognition [1]. A solution of such Image classification Problem by yielding best outcomes is through a technique, called as Transfer Learning. Transfer Learning has another term i.e Inductive Transfer. It is a major research problem in Machine learning. The concept behind traditional machine learning method is training the data and testing data. Then the data are taken from the same domain, so that the input feature space and data distribution characteristics are same [1]. Transfer learning is a method, in which one problem model is applied on the second problem in the similar manner. Computer Vision finds Transfer Learning suitable for building accurate model. Training Time gets minimized in Transfer Learning, which is considered as one of the advantage with Transfer Learning. Traditional learning is fully dependent on some specific datasets, tasks, and training models. There is no requirement of knowledge retaintion. It cannot be changeable from one approach to another. But in case of Transfer Learning, weights and features can be leveraged from old trained models to new trained models. Also some problems like less data for the new task can be solved. Transfer learning can use knowledge from old tasks, apply to new [2].

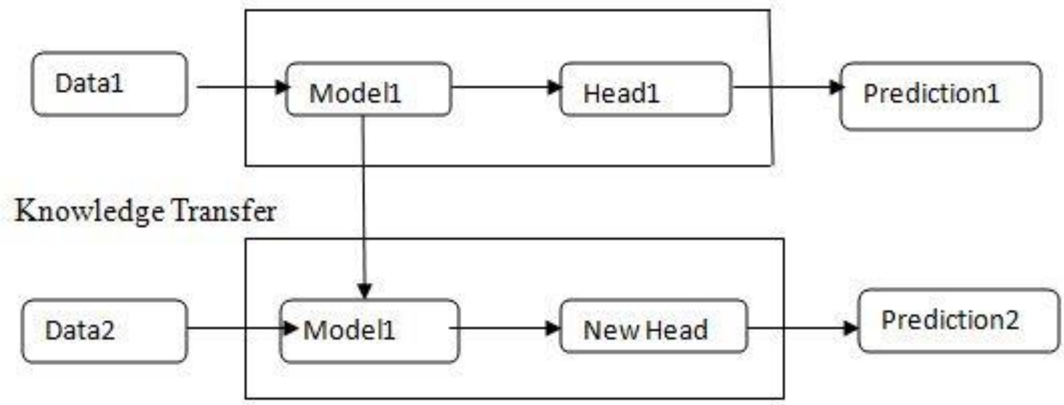

Figure 1- Transfer Learning

Types of Transfer Learning

The categorization of Transfer Learning Methods is made on the basis of traditional Machine Learning algorithms.

- Inductive Transfer Learning: The source and destination are same. But the source and target tasks are different from each other [3]. The algorithm has the objective to use the inductive biases of the source domain to improve the target task. If the source domain contains labeled data, it can be divided into multitask learning and self taught learning
- Unsupervised Transfer Learning: it is same as inductive transfer. It has a focus on unsupervised tasks in the destination domain. The source and destination domains are equal, but the tasks are not the same. The labeled data is not available in either of the domains [3].
- Transductive Transfer Learning: There are similarities between the source and target tasks, but the corresponding domains are different. The source domain has a number of labeled data and target domain has no labelled data. The subcategories coming out of it refers to settings where either the feature spaces are different or the marginal probabilities are dissimilar[3][4].

Deep Learning Model: Deep Learning models are also known as inductive learning. The inductive learning algorithms infers mapping from training examples. In classification, the model has mapping between input features and class labels. For the generalization of unseen data, algorithm has set of assumptions related to the distribution of the training data [4][5]. The assumptions are known as inductive bias. The inductive bias has many numbers of factors.

Deep Transfer Learning Approaches

Deep learning has made considerable progress. It has strength to handle complex problems and yield outcomes. The training time and the amount of data required for deep learning systems are more than that of traditional ML systems. A number of deep learning networks with better performances are available. It has applications with computer vision and natural language processing (NLP). These are pretrained networks or pre trained models. These are acting as basis of transfer learning in the context of deep learning. These are also called as deep transfer learning [6].

Deep learning system models are layered architectures. It can learn hierarchical representations of layered features. These layers are connected to a last layer i.e fully connected layer, in case of supervised learning to get the final output. The layered architecture use a pre trained network without its final layer as a fixed feature extractor for other tasks. The pre trained models include Inception V3 or VGG. AlexNet can be used without its final classification layer. It transforms images from a new domain task into a 4096-dimensional vector based on its hidden states. It enables extracting features from a new domain task by utilizing the knowledge from a source domain task. Pre trained models are usually shared in form of parameters or weights [7]. Pre trained models are available for use through different means. The deep learning Python library, keras, provides an interface to download some popular models. Pre trained models can also be accessed from the web due to open source.

Introduction To Biometric System and the Experimental Methodologies

Identifying individuals in such a manner with the help of biometric data is known as biometric recognition system. Biometric Recognition System has the advantages of authenticating individuals. For example, a finger tip can be taken as authenticated. it consists of ridge patterns, valleys. Two persons cannot have the similar pattern. If any cuts or any losses occur to the fingerprint, then the accuracy of recognition is affected. Fingerprint consists of ridges and valleys [7][8]. Unique patterns can be formed out of these valleys and ridges. Fingerprint has a portion called minutiae. It generate the authenticity and uniqueness of fingerprint. Another object of authentication is the palm print. It consists of wrinkles, delta points, geometry features etc. Another important recognition element is ear. It can be taken as biometric recognition, as it has helix, lobe etc. Though the left and right portion of ear are similar in case of a human being, but sizes tend to be changeable. Now a days, signatures are taken as the authentication [9][10].

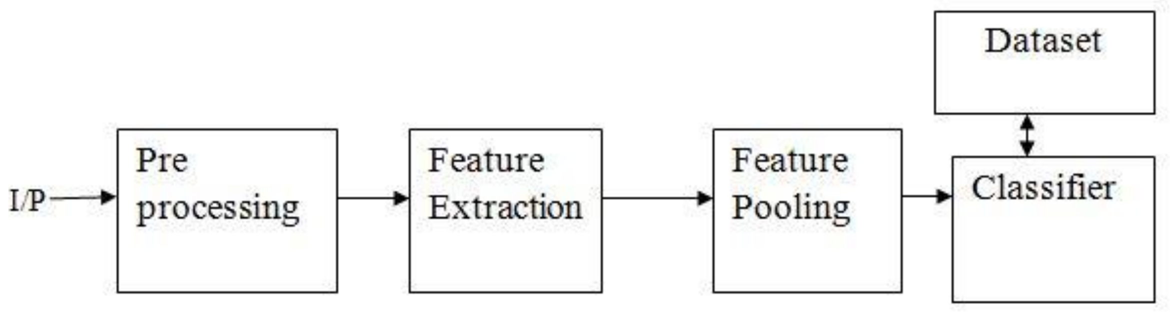

Fig.2- Schematic Diagram of Biometric System

Biometric Recognition System has the following steps,

1. Different cameras capture a number of image data. Then the data are pre processed.
2. Features are extracted from given images
3. After Feature extraction, classifier is used for the recognition purpose

Challenges were confronted with such process included in biometric system. For which deep learning based models came into existence as a solution.

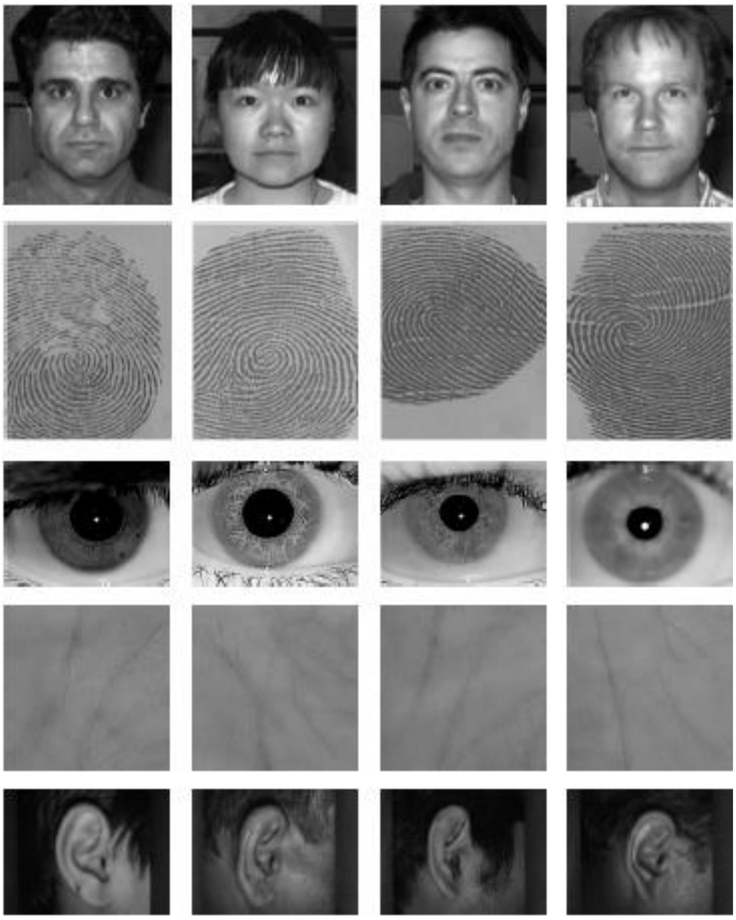

Fig. 3- Images for Biometrics [8] [9] [10]

Another important recognition element is Iris. The iris structure is for the unique identification as well as recognition. It helps in providing high system accuracy because of the pupil and sclera present in iris. For computer vision, some popular models include ResNet-50, VGG-16, VGG-19, Inception V3, XCeption etc. For Natural Language Processing tasks, Word2Vec, GloVe, FastText are the famous models. Iris recognition is one of the most accurate identification system [10][11]. For problem solving, the image resolutions are to be worked on. It is related to iris resolution. Single image super resolution is a kind of problem. Its objective is to extract the high resolution images from the low resolution ones. It can be done with the help of regression functions, sparse dictionary etc. PCA and Bayesian methods are also inclusive of it. Transfer Learning can also be useful for the Iris Recognition for single image super resolution. The only constraint with it is to know the correct use of database for performing transfer learning method to get patterns applied in target database. The CASIAIris V3 can be used as the iris dataset to experiment whether the use of transfer learning is correct or not with a set of training databases. This dataset is used for biometric test. It contains images with pixels of 280X320 [11]. High resolution camera used for this. The experimental setup resulted 396 no. of images of eyes. First of all, all images got resized with sclera radius from the database. Then it was cropped with a region of 231X231. All these are included in preprocessing step [13]. After the pre processing step, it was evaluated with the rest no. of images from the database. To do so,database is getting devided into two parts. One contains first three user images[14][15]. These are called registration images. The second one contains the rest authenticated images to be trained with CNN for Transfer Learning Evaluations [16].

Face is one among the popularly used biometric systems. A Person's Identification with its own image is usable for authentication. It is developed with smart systems to identify the faces for biometric purposes along with authentications [12].

Haar Cascade Classifiers are used for the feature extraction. The xml file of Haar Cascade are downloaded from the Google, placed in directory. A features sets are encoded within it. Faces are detected with classifier, [12]. LBPH algorithm is a simple and efficient text description operator, where the picture pixels are marked with threshold value of each pixel and produce a binary number. Then the Local Binary Pattern Histogram is combined with histogram and characterizes the face images with a simple data vector [12].

Face Recognition System consists of the following processes:

1. Face Identification- A System finds the face position in an image or video. It gives the coordinates of a bounding box for each of the image taken.
2. Face Alignment- The objective is to crop and scale the face with the help of a number of reference points, which are located at a fixed locations in the image [12].It is a Computer Vision method of finding geometrical human facial structure. By giving the facial size and location, it finds the structure of the components of face like ears, eyes and nose.
3. Feature Extraction- Here the pixel values of a face are mapped into a compact feature vector, which is considered a template.
4. Feature Matching- Here two templates are compared and result score, which specifies the likelihood, which belong to the same subject.
5. Database of enrolled users. It will match the face from the given datasets of enrolled users. [12]

Conclusion

This paper describes about the summary on Transfer Learning approaches and use of it in biometric system. Also this paper covers the mostly usable biometrics and their implementations with thw help of different models.

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