ML in the field of Biometrics :

As we know due to their ability to mine ,analyse and interpret large datasets ML methods have been applied to many disciplines .And the field of Biometrics is no exception. The basis for any biometrics method is some kind of matching methods which typically are one to one in case of verification and one to many in case of identification .In this regard records show that ML methods improved the performance of biometrics systems .

First let’s see how the broad classifications of Ml divisions have their application in biometrics .

Supervised learning has been helping several biometric applications through a large number of algorithms. Some of the algorithms are Convolutional neural nets, Kernel Methods, logistic regression and Decision trees.
Facial recognition uses the ‘Decision trees’ algorithm for the accurate face recognition biometrics, and the latest surveys show that it gives 100% accuracy on the Facial Recognition Technology Database (FERET). Speech emotion recognition uses Support Vector Machines (SVM) algorithm and the ‘Kernel Method’ approach is used for facial emotion recognition. The classifier can recognize up to 6 facial emotions with an efficiency rate of 98.6% on the JAFFE database.

Unsupervised machine learning implemented in biometrics ensures better learning methods, allows better classification and the accurate positioning of biometric features. Unsupervised learning can be used for extracting the full automatic finger vein pattern.

A clustering Algorithm named ‘nearest neighbour clustering algorithm’ was proposed for retina pattern matching and it has been successfully used for retina vessel segmentation. Unsupervised learning algorithms were also used for voice activity source detection and the clustering algorithm was used to extract the biometric voice features from energy signals.

Now let's look into some established work done in biometrics using Machine Learning methods

In [1], the authors proposed a one-shot learning facial recognition method (DeepFace) based on deep Siamese network and support vector machine (SVM) classifiers. They used three datasets to train and test their model. Each dataset consists of pairs of images that belong either to the same person or different persons. A complex 3D alignment process was applied to each pair of images and then fed to the Siamese network for extracting features from each image. The absolute difference between the features of each pair of images is computed. Next a fully connected layer is used to map the result into a single logistic unit based on a binary classifier to classify each pair into the same-person or different- person classes. This is followed by application of the SVM instead of logistic regression units to complete the classification process. The (SFC) dataset was used to train the proposed method, and the (LFW) dataset and the (YTF) dataset were used to test the proposed method. The results indicated that the proposed method outperforms the state-of-the –art technique [1]achieving performance close to humans was (the accuracy of the proposed method 97.35% in LFW dataset compared to 97.5% human cropped, and 91.4% in YTF dataset).

In [2], the deep CNN based on triplet inputs was proposed for one shot-learning. The authors proposed to use 3 input images (person, false positive person, false negative person) to train the CNN. The features are calculated for each of 3 images and then a difference of (person, positive person) features, and (person, negative person) features were calculated to compute very high accuracy ≈99% compared to 97% reported in [1]. This method tested with slandered face recognition datasets (LFW) dataset, (YFT) and achieved the state-of-the-art in recognition performance (LFW accuracy 99.63%, and YFT accuracy 95.12%). Also, this method used minimal alignment compared to [1] which used a complex 3D alignment to extract the facial features. The authors used the proposed method as another application to cluster a users personal photos into groups of people with the same identity based on agglomerative clustering (This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy [3]). This application showed no sensitivity to occlusion, lighting, pose and even age variations. As an application of semanese Neural Net, twin-face verification was proposed in [4].

The authors in [5] proposed a supervised deep learning structure called Deep Irisfor iris verification based on pair filter layer (PFL) and convolutional layers. Two standard datasets (Q-FIRE and e CASIA cross sensor datasets) were used in this work. These datasets consist of heterogeneous iris images (collected from different sensors, different distances (resolutions), and different illumination) labelled in two classification classes. An input to the Deep learning network is a pair of images which belong to either the same person or different persons. The similarity map is generated by involving a pairwise filter layer as a first layer to convolve the images and summarise the feature map by using a number of filters. Three different structures based on PFL were proposed and tested to produce the best iris verification system, and then the results were compared with the state-of-the-art techniques. The results from the best structure showed increasing the accuracy and decreasing the Equal Error Rate (EER) to 1/10 compared to other methods with a high genuine accept rate (GAR) (≈95%)and very low FAR (≈ 10-4).

As everything good comes at a cost there are some **Challenges of using ML in biometrics** as well.Let's take a look at them too.
And by the way it is more appropriate to consider the following points as challenges of using ML in biometrics instead of disadvantages due to rapid developments in the ML field which include optimised structures, new deep structures, advanced and cloud-based devices for accelerating computations.

1. To produce a good model needs a general and large dataset.
2. No general ML algorithms and structure can be used for all biometric systems.
3. Unreliable results due to noisy environments, sensors problems, and/or acquisition problems.
4. Optimising ML parameters is not easy
5. Time consuming: Need preprocessing methods to prepare and improve the quality of datasets. Also, some of these methods are based on deep learning methods. For example, face recognition processes need face detection, segmentation, denoising, and pose and illumination corrections.
6. Huge memory to store the database.
7. Need continuous developments of the used method to resist attackers and hackers.
8. Need to develop anti spoofing methods due to increasing availability of synthesised data.
9. Although some DL models achieved a high accuracy, still additional data is required to develop and retrain identification and recognition models.

References:

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[3]Wikipedia:Hierarchical Clustering https://en.wikipedia.org/wiki/Hierarchical_clustering

[4] Sun X, Torfi A, and Nasrabadi N 2018, “Deep Learning in Biometrics, Chapter 3: Deep Siamese Convolutional Neural Networks for Identical Twins and Look-Alike Identification”, 5 March 2018