Can we recognize horses by their ocular biometric traits using deep convolutional neural networks?

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ABSTRACT

This paper aims at determining the viability of horse recognition by the means of ocular biometrics and deep convolutional neural networks (deep CNNs). Fast and accurate identification of race horses before racing is crucial for ensuring that exactly the horses that were declared are participating, using methods that are non-invasive and friendly to these delicate animals. As typical iris recognition methods require lot of fine-tuning of the method parameters and high-quality data, CNNs seem like a natural candidate to be applied for recognition thanks to their potentially excellent abilities in describing texture, combined with ease of implementation in an end-to-end manner. Also, with such approach we can easily utilize both iris and periocular features without constructing complicated algorithms for each. We thus present a simple CNN classifier, able to correctly identify almost 80% of the samples in an identification scenario, and give equal error rate (EER) of less than 10% in a verification scenario.

Keywords: iris recognition, ocular biometrics, horses, convolutional networks, deep learning

1. INTRODUCTION AND PAST WORK

Typical ways of identifying horses involve external features, such as hair patterns, micro chip implants, tattoos applied on the upper lip, or even burnt or frozen markings on the skin. Some of them inflict pain to the animal, such as tags or implants, while some of them are not 100% accurate and prone to changing with time, such as determining identity using hair patterns or coloring. As race horses are identified shortly before the race, their identification has to be fast and accurate. Also, these animals are very delicate and can become nervous if touched, therefore non-invasive and non-contact methods of identification are preferred.

In 2001, a system for identifying horses employing iris recognition was proposed by Suzaki *et al.*[1] A few important issues regarding equine iris recognition were discussed, namely difficulties in obtaining sharp images due to horse's rapid movements, large variations in pupil size, and coarse iris pattern folds (when compared with human iris). To cope with these problems, a method for picking suitable samples from a series of images is used, based on the illumination reflection shape and size. This is to select those being in focus and containing the whole eye. Due to shape of the pupil and the iris of a horse that is difficult from a classic iris recognition point of view, the iris area is modeled using non-oval shapes, using only the lower part of the iris, which is not obstructed by the *granula iridica* (a melanin pigment concentration typically appearing over a horse eye's top pupil-iris boundary). Feature extraction is carried out twofold by convolving the iris pattern with a Gabor filter in both angular and radial directions and binarizing the amplitude, effectively computing two separate iris codes. This is done to account for changes in the iris folds in both directions, as horses are said to exhibit more iris texture variability in the radial direction than humans, as they mostly exhibit circumferential iris folds. Computing

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fractional Hamming distance is employed to calculate the similarity between the respective iris codes of two horse irides. Experiments were carried out using a database of 98 enrolled horse eyes, out of which 68 were then subject to testing (verification). Authors report very low FAR values, yet rather high FRR values of about 14%, which are then partially alleviated by allowing multiple verification attempts in a single transaction.

Other applications of iris biometrics in animals mainly relate to cattle identification. Wang *et al.*[2] outline a recognition system for tracing sources of infection in large animals. The solution is said to employ 2D Gabor filtering as proposed by Daugman,[3] but no experimental results or feasibility of the prototype are divulged in the paper. Sun *et al.*[4] aim at implementing reliable iris recognition in cattle. Multiple challenges that arise specifically when designing non-cooperative bovine iris recognition are reported, namely large variance of image rotation and scaling, non-circular irides and pupils, off-angle presentations and more reflections when compared with typical cooperative iris recognition in human subjects. Image segmentation is said to employ active contours. Iris features are extracted with scale-invariant feature transform (SIFT) and then a histogram representation of these features is generated for each iris using the bag-of-features technique for reducing computational complexity (compared with calculating Euclidean distance between individual SIFT-derived keypoints). Matching is carried out by calculating distances between these histograms. Correct recognition rate of 98.15% is reported. Recently, a system for iris recognition in cows was proposed by Lu *et al.*,[5] employing 2D Complex Wavelet Transform (2D-CTW) for feature extraction and calculating the fractional Hamming distance for the matching stage. Results with Equal Error Rate (EER) of 1.55% in the verification scenario and Correct Recognition Rate (CRR) of 98.33% in the identification scenario are reported.

A common factor of all the methods discussed above is the need for knowledge about the characteristics of an object (here, an animal iris) that is used for recognition, and construct a fine-tuned algorithm that deals specifically with this particular case. There are some difficulties of such approaches – most prominently trouble with data of varying quality, such as off-angle images, out of focus images, or those that do not depict the whole portion of the iris. In our work, we aim at exploring the possibilities that are offered by deep convolutional neural networks (deep CNNs), which have recently been shown to achieve excellent results in complicated recognition problems, such as classification of natural images[6] [7] [8] and image segmentation tasks.[9] [10] [11] [12] Recently, also applications for iris image segmentation[13] and iris recognition have emerged.[14] Periocular recognition using CNNs was studied by Zhao *et al.*[15] CNNs are known for their capability to describe the textural and semantic details of an unprocessed input image and provide class-wise prediction in an end-to-end manner. Therefore, we believe them to be useful for the task of iris and periocular recognition.

2. ANATOMICAL BACKGROUND

Anatomy of the anterior segment of a horse eyeball is similar to this of a human. The most obvious difference is size, with horse's globe measuring from 48.5 to 54 millimeters along the horizontal axis and from 37.5 to 44 millimeters along the vertical axis. Depth of a typical horse eyeball usually falls in between 41.5 and 51 millimeters.[16] There are also a few other differences that may be considered important for biometrics (Fig. 1).

The palpebral fissure in horses is horizontally oval. There are no cilia (eyelashes) on the lower eyelid, but they are well developed on the upper eyelid. Vibrissae are also present. Those single, thick sensing hairs are located on the base of the eyelids. Both upper and lower eyelid adheres tightly to the globe, except for the medial canthus near the lacrimal caruncle, where a protuberance of varying size is usually present. The lateral canthus is visibly more rounded than in human eye. There is a relatively small portion of exposed sclera. The lateral part of conjunctiva is often pigmented. Between the globe and the medial canthus there is a free margin of the third eyelid (membrana nicitans). It may or may not be pigmented and it usually depends on the color of the coat. Third eyelid is so extensive that it is capable of covering the entire cornea.[17]

The largest part of the eyeball surface that can be normally observed is comprised of the cornea, which is elliptical in shape with regular, smooth, and shiny surface. The horizontal axis of cornea is longer than the vertical axis (28-34mm and 23-17mm, respectively). In human eyes, this difference is much smaller. As functions of the cornea include transmission of light it has to be fully transparent. This transparency is attributed to anatomical factors, such as the absence of blood vessels, nonkeratinized surface, lack of pigmentation and stromal collagen fibrils in specific size and organization. Behind the cornea the anterior chamber is located, filled with optically clear aqueous humour.[16,17]

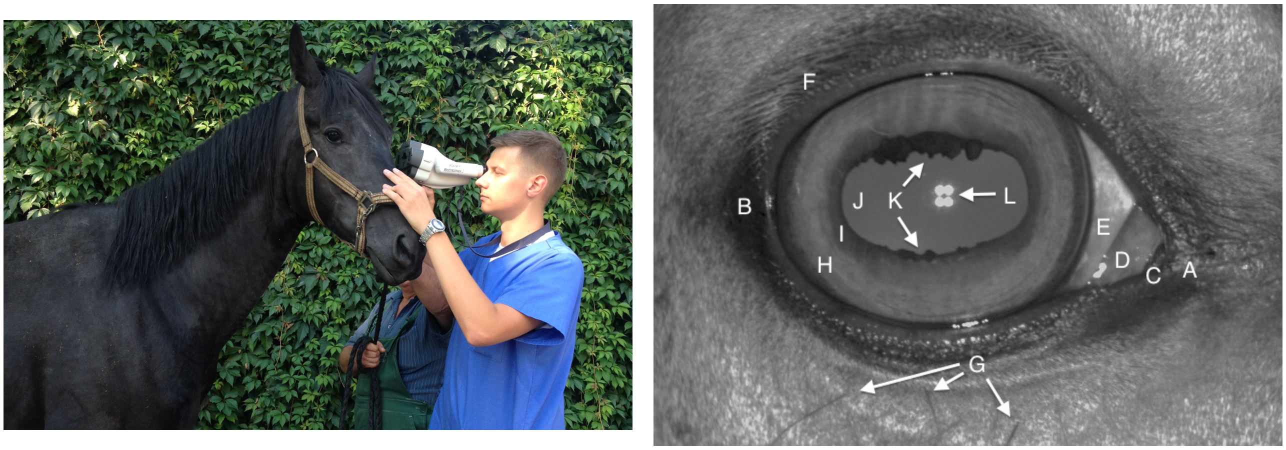

Figure 1: **Left:** Ophthalmological examination performed in a horse. **Right:** Surface anatomy of equine eye and adnexa photographed under near-infrared illumination: (A) medial canthus, (B) lateral canthus, (C) lacrimal caruncle, (D) free margin of membrana nictitans, (E) sclera, (F) cilia, (G) vibrissae, (H) ciliary zone of iris, (I) pupillary zone of iris, (J) pupil, (K) granulae iridica, (L) infrared light source reflection

The iris separates the anterior chamber of the globe from the posterior chamber. It extends centrally from the ciliary body and partially covers the anterior surface of the lens. A central aperture of the iris constitutes the pupil. The pupil can vary in size. Dilation or constriction of the pupil affects the amount of light entering the eyeball. In horses, the pupil is rod-shaped with a long horizontal axis. Along the dorsal (upper) pupillary margin there are well developed round black masses called granula iridica (corpora nigra). Sometimes similar features can exist on the ventral (lower) edge of the pupil. Anterior iris surface is composed of two zones, namely the central pupillary zone and a peripheral ciliary zone. Between these zones, the collarette is located. Collarette is most prominent with moderate dilation of the pupil. The pupillary zone can be more pigmented and thinner than the rest of the iris. Color of the iris depends on the amount of iridal stroma pigmentation, the type of pigmentation, vascularization, and also on the shape and size of collagen fibers found in the stroma. In horses it can range from dark brown to gold, or even blue. The original surface shape of iris is determined by specific system of blood vessels and collagen fibers.[16 17]

3. EXPERIMENTAL STUDY

3.1 Database

A dataset of equine eye images acquired under near illumination was created by the authors for the purpose of this study. Data collection was performed during routine ophthalmological examination of the animals (see Fig. 1 on the left). Pupil-LR (from SIEM Bio-Medicale) device was employed. It includes an infrared-sensitive camera which can deliver continuous infrared illumination and enables concurrent imaging of the anterior eye segment at 60 frames per second. Data collection was performed in two sessions, with each session lasting 10 seconds. When performing experiments described in this paper, there were **9 classes** (nine horse eyes) in the dataset. We also performed some censoring of the data, to exclude images that were out of focus and those do not representing the eye region (due to blinking or rapid horse movements). The final set contains **7250 images**. Sample image is shown in Fig. 1 on the right, additionally annotated to provide description of the eye anatomy.

3.2 HorseNet-4: network implementation, training and evaluation

For the purpose of recognizing horse eyes, a simple architecture of deep convolutional neural network has been built – HorseNet-4, Fig. 2. It consists of four convolutional layers, two with kernel size of 3×3, and two with kernel size of 5×5, with ReLU activation functions. After each convolutional layer, a spatial max pooling layer with pool size of 2×2 is applied. Finally, two fully connected layers serve as a classifier for features extracted by the convolutional layers. The second fully connected layer outputs class-wise probability via the Softmax activation function.

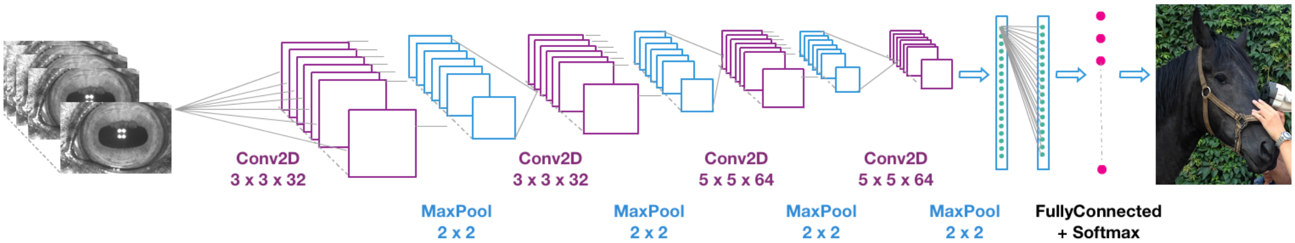

Figure 2: Architecture of the HorseNet-4 model. Batch normalization and activations are omitted for clarity. Horse eye images are the input, while the last Softmax dense layer outputs class-wise probability that the sample belongs to a given animal.

The model was trained using all samples from the first acquisition session. The only preprocessing applied to the data involved 4× downsampling. We used learning rate of 0.01, decay of 10^{-6} and momentum of 0.9. Batch normalization and dropout techniques were used. The former enables faster network convergence by reducing differences in the distributions of layer input,[18] the latter helps dealing with network overfitting by randomly removing units with their connections from fully connected layers.[19] Batch normalization was applied after each max pooling layer, while dropout was used after the first fully connected layer (for training only). Evaluation was conducted using all the samples from the second data acquisition session.

The implementation of the network was performed with a Python[20] + OpenCV[21] environment, using the Keras framework for deep learning[22] with TensorFlow backend.[23] All calculations were done on an Intel Core i5 notebook running at 2.7 GHz. Training of the model takes approximately 5 minutes per epoch, while the average prediction time per sample is 0.03 seconds.

4. RESULTS AND DISCUSSION

We were able to achieve correct recognition rate of almost 80% on the validation set when using the above HorseNet-4 architecture. Unsurprisingly, the accuracy on the training set is perfect, reaching 100% as the network learns how to ideally differentiate between samples from the training data. Fig. 3a shows training and validation accuracy of the model. Receiver Operating Characteristics (ROC curves) are commonly used for describing the accuracy of a classifier and are shown in Fig. 3b.

This shows that we have constructed a viable classifier based on deep convolutional neural networks for animal identification using ocular biometrics. The limitations of this study include a rather small database, especially class-wise. This, however, will be alleviated in future studies, as the data collection continues. Results presented in this paper are promising and while still requiring more work, show a possibility of employing DCNNs for horse identification. As approaches based on neural networks are known for their flexibility, there are many potential applications for our solution, as with good confidence any eye region will work, such as these of different animals, and even humans.

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The work while preparing this study was divided as follows: MS collected the database of horse iris images, censored the dataset, consulted on the veterinary-related matters and wrote approximately 30% of the paper. MT came up with the idea of employing convolutional neural networks for the purpose of recognizing horses, handled the network implementation and experiments, and wrote approximately 70% of the paper.

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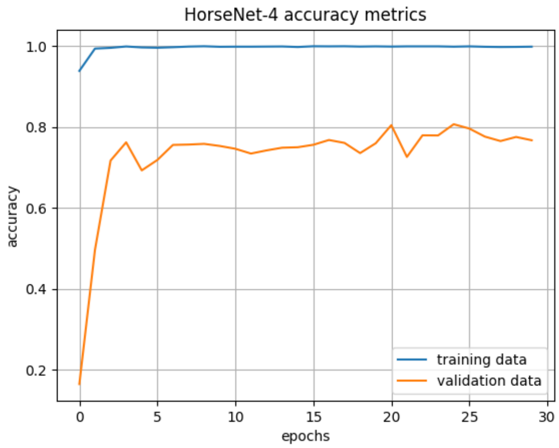
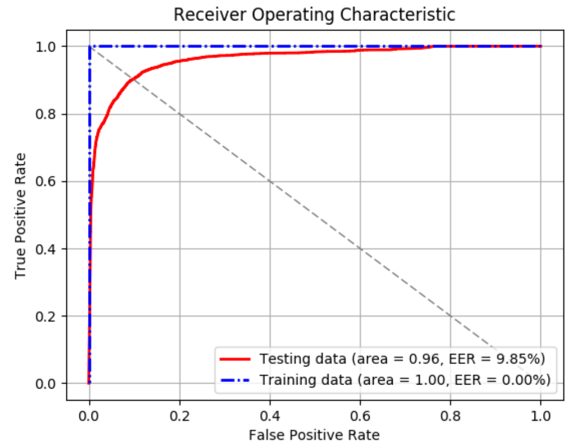


(a) Classification accuracy on the training and validation data in respect to the number of epochs.



(b) ROC curves plotted for training and testing data. Equal Error Rate (EER) values are also shown.

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