Stature estimation using Convolutional Neural Networks based on footprints and measurements

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***Abstract*—Recently CNN models are widely used for regression or classification tasks in different research fields. This study proposes a method for stature estimation that can be used to link scenes of crime. Basically, it takes as inputs to process the both footprint sides in CNNs and its measurements in MLP. The proposed algorithm has been tested on a dataset composed of 537 people footprint samples provided by the third party, and the result indicated a RMSE 3.57.**

Keywords—CNN, footprint, Forensic anthropology, stature estimation.

I. Introduction

Forensic anthropometry determines an important role in the identification of human parts in many fields, particularly in identification of people [1]. There are many studies to find a relationship between human body parts and the individual's height. These approaches can be reviewed in Atamturk et al 2008, Jasuja et al 1997, Kanchan et al 2008 and Krishan 2008 [2][3][4][5]. As well, foot measurements such as length and breadth are significant to recognize stature (Krishan 2007) [6]. Moreover, there are other variables like sex, age, and weight that could be possible related to each other [7]. Even among different populations in the world, this task becomes difficult to predict a relationship of stature. Sarah Reel et al developed a pragmatic method for measuring footprints that could withstand the challenges of rigorous reliability testing in order to propose the method as an acceptable baseline technique for footprint comparison in further research and for forensic comparison and analysis [8]. Therefore, this research proposes a method for stature estimation using CNNs and footprint measurements at the same time. The rest of the paper is organized as follows. Section 2 reviews related works on CNN models and regression techniques. Section 3 presents the proposed method. Section 4 provides the experimental results, followed by the conclusions in Section 5.

II. Related Work

Given the complexity of this task, this field is still novel in methods that involve deep neural networks. For that reason, most of the related work utilizes types of regression techniques and show statistical results. Khairulmazidah K. et al determined foot length has a strong correlation with stature than shoeprint length for both sides of the feet [9]. In addition, prediction equations were developed to estimate the stature using linear regression analysis of foot length and shoeprint length and concludes that foot lengths give better prediction than shoeprint length. See Table I.

TABLE I. LINEAR REGRESSION EQUATIONS FOR STATURE ESTIMATION

Gender	Variable	Equation	*SEE (cm)
Males (n=100)	*RFL	Y= 84.663 + 3.321(X)	4.936
	*LFL	Y= 92.819 + 2.972(X)	5.182
	*RSL	Y= 93.182 + 2.643(X)	5.972
	*LSL	Y= 94.972 + 2.573(X)	5.928
Females (n=100)	*RFL	Y= 86.554 + 3.115(X)	4.483
	*LFL	Y= 84.325 + 3.214(X)	4.394
	*RSL	Y= 100.609+2.258(X)	4.991
	*LSL	Y= 101.294+2.227(X)	4.991
Unknown (n=200)	*RFL	Y= 72.446 + 3.783(X)	4.819
	*LFL	Y= 76.726 + 3.589(X)	4.899
	*RSL	Y= 84.495 + 2.936(X)	5.525
	*LSL	Y= 85.186 + 2.904(X)	5.562

*SEE, standard error of estimate, *RFL, right foot length, *LFL, left foot length, *RSL, right shoeprint length, *LSL, left shoeprint length

Recently, CNN has become one of the most popular neural networks in deep learning approaches. Due to these networks are very good feature extractors. This means that you can extract useful attributes from an already trained CNN with its trained weights by feeding your data on each level and tune the CNN a bit for the specific task. A typical CNN architecture is shown in Figure 1.

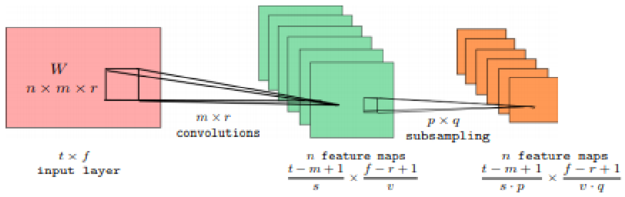


Fig. 1. Convolutional network architecture

However, if the model is trained for regression predictions, then it process to remove the fully-connected softmax classifier layer typically used for classification and replace it a fully-connected layer with a single node along with a linear activation function. In this way, it changes to train the model with continuous value prediction loss function such as mean squared error, mean absolute error, mean absolute percentage error, etc.

III. Model Design

A. Preprocessing dataset

The dataset collects 534 footprints samples with annotations in Json File that contain region points and metadata such as age, weight, and height of the person. See Figure 2.

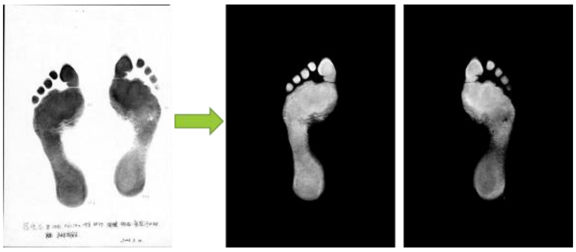


Fig. 2. Example of raw footprint and after processing.

The algorithm for processing footprints was develop in MATLAB. First step was to decode the Json annotations and extract two parts which are metadata and region points. With that information, it evaluated the image orientation since some of them are in different direction and rotated in case it is required. After that, the image was cropped for each side getting the left and right footprints. Continually, the program run a vertical alignment method to calculate some measurements (length, breath sole and breath heel). Finally, write the footprint images. This allowed to get clean images for inputs and train the CNN model later. The flow diagram is shown in Figure 3.

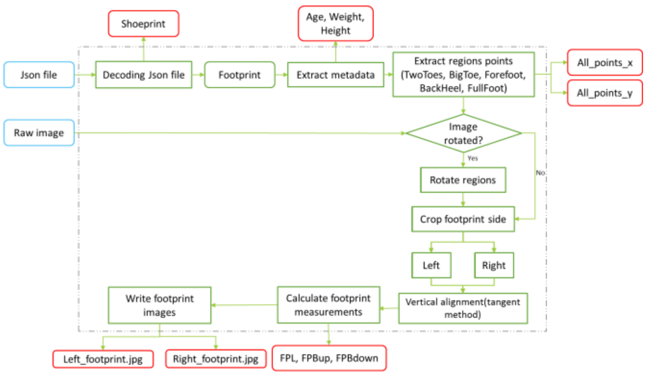


Fig. 3. Flow diagram for preprocessing dataset

B. Footprint measurements by tangent method

In order to correctly calculate the measurements, all the footprints were aligned vertically by tangent method and translated to the center of image. This method is explained in the following procedure.

- Get tangent lines between regions c and d. Use convex hull function to calculate L1-L2 and R1-R2 lines.
- Determine angle between tangent lines theta=α-β. Then compute the rotation angle=90-α+(theta/2) for footprint. there is a condition to evaluate positive or negative angle. If L2x>L1x then the slope is positive, on the other case is negative. See Figure 4.
- Rotate original image and calculate de distance between the top and bottom pixel value different from the background that represents the footprint length.
- In the same way, calculate the distances between L2-R2 and L1-R1 that mean the footprint breath sole and breath heel respectively.

At the beginning, it was considered for vertical alignment to take the union of all regions of the foot but because certain images produced error in the tangent lines detection. It was decided only to take the regions of BigToe plus ForeFoot.

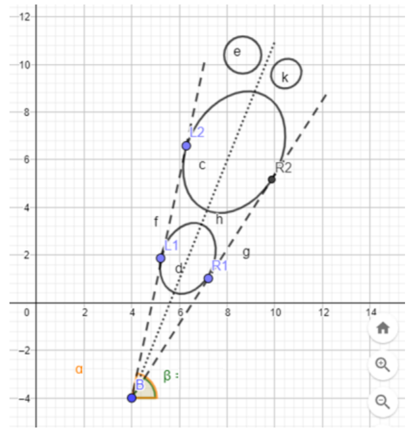
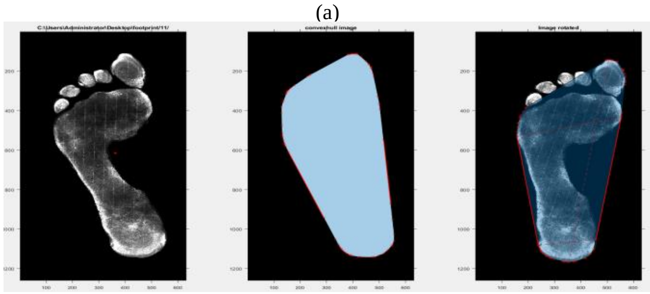


Fig. 4. Tangent method representation

The figure 5 shows the steps procedure previously explained to calculate the measurements for inputs in the general model.

(a)



(b)

Fig. 5. (a) Crop footprint sides result (b) Vertical alignment result

C. Fooprint model

To solve this regression task and obtain the stature of the person, the footprint model is divided into three parts, which two of them are images data (footprint right and left) and one is numeric data (6 footprint measurements). See Figure 6. Thereby, the numeric input pass to a Multilayer Perceptron model defined by two dense layers with Relu activation and linear regression output. Regarding to image inputs, these were training in Convolutional Neural Network. This model consists in 3 blocks of layers defined by Conv3x3 – Relu – BNorm with filter sizes 32, 64,128 and MaxPooling 2x2. After that, apply a FC, Relu, BNorm and Dropout layers to finally finish with a linear regression output. Then the footprint model concatenates each output part and apply a FC plus a linear activation. The model was developed in Keras framework.

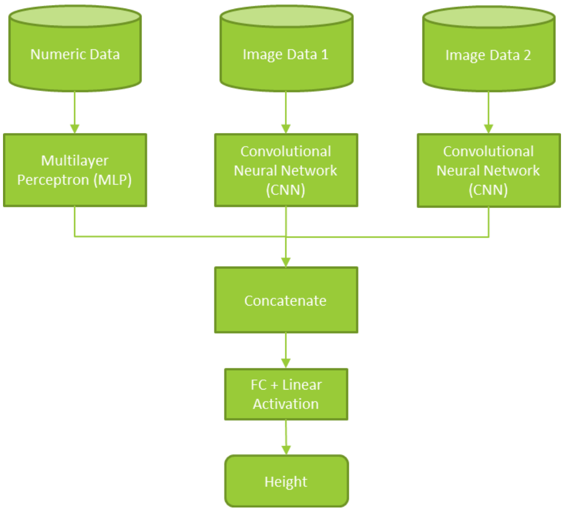


Fig. 6. Footprint model for stature stimation

IV. EXPERIMENT AND RESULTS

The model was trained with Adam and Adabound optimizer. In addition to this, the input size image was set 128x96. For the first case, the hyperparameters were set as learning rate 0.001, decay 0.001/200, beta1 0.9, beta2 0.999 and no epsilon value. While Adabound was set as learning rate 0.001, final learning rate 0.1, gamma 0.1, weight_decay=0.1 and amsbound False. Besides, it was tested two cases dividing the test set into 20% and 10% of total samples. The results are shown in Table II and Table III respectively. These tables indicate the RMSE value for different batch size and epochs got in the training model. The best RMSE result 3.57 was found in 10% split test set for batch size 16 and epoch 300.

TABLE II. RMSE RESULTS MODEL FOR 20% SPLIT TEST

	Batch size / #epoch	**8**	**16**	**32**	**64**
Adam optimizer	**100**	4.8602	6.3152	26.8564	14.1451
	300	4.2930	**4.2483**	4.2552	6.4386
	500	4.2608	4.5338	4.6756	5.4608
Adabound optimizer	**100**	5.5663	4.4936	5.1737	7.7120
	300	4.6720	**4.0569**	4.5371	4.8314
	500	4.2175	4.4503	4.4594	4.0824

TABLE III. RMSE RESULTS MODEL FOR 10% SPLIT TEST

	Batch size / #epoch	**16**	**32**
Adam optimizer	**100**	4.6140	5.0036
	300	**3.7162**	4.1273
	500	4.6548	3.9786
Adabound optimizer	**100**	3.8572	4.5757
	300	**3.5681**	4.2277
	500	3.9045	4.1951

During the training, it observed the Adabound optimizer tends to collapse the model if the hyperparameters are not tuning correctly in the split test 10%. While Adam optimizer produces many high peaks loss during the training model. Figure 7 illustrates the model loss for training and testing.

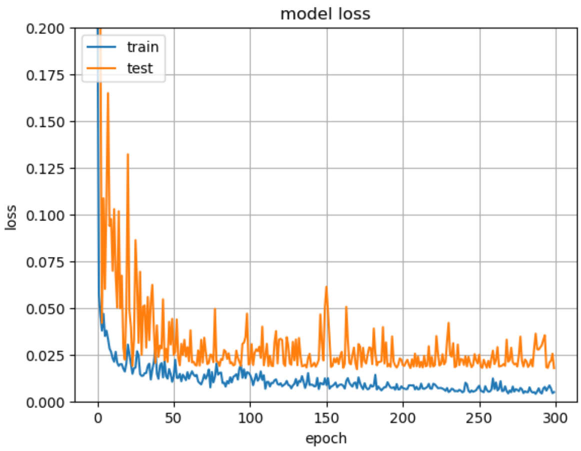


Fig. 7. Footprint model loss

For a comparison of model performance, it was also trained the footprint measurements and height labels by GBR algorithm that indicates a RMSE 3.83. See Table IV.

TABLE IV. RMSE RESULT USING GRADIENT BOOSTING REGRESSOR

Id	height	data	residuals	residuals**
428	165.0569	165	-0.0569	0.0032
435	169.5224	168	-1.5224	2.3177
442	169.8619	168	-1.8619	3.4666
446	166.0769	162	-4.0769	16.6214
452	169.833	162	-7.8330	61.3566
460	167.0313	165	-2.0313	4.1263
461	166.8313	165	-1.8313	3.3538
465	173.101	168	-5.1010	26.0206
476	165.109	165	-0.1090	0.0119
481	166.2914	165	-1.2914	1.6678
483	166.2396	167	0.7604	0.5782
486	168.685	163	-5.6850	32.3198
487	169.4347	168	-1.4347	2.0584
492	164.8395	165	0.1605	0.0257

498	170.2032	165	-5.2032	27.0728
499	179.1365	171	-8.1365	66.2026
500	169.5144	172	2.4856	6.1780
501	164.7477	168	3.2523	10.5774

Sum	263.9587
RMSE	3.8294

V. CONCLUSION

This study proposed a simple multi-input numeric and images model for stature estimation using CNNs. The algorithm has been tested on the dataset that contains 534 people footprints. With the best tuning parameters, it was found a RMSE 3.57 that comparing with other boosting algorithms or multilinear regressions has a better performance. For future work, it is planned to customize a CNN model appropriately for footprints and generalize it for shoeprints that have more features and parameters to estimate age, height or weight.

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