A27 New Solutions for Old Problems? Examining Machine Learning as a Strategy for Age-at-Death Estimation

Melissa Ann Brown, MA, Western Michigan University, Kalamazoo, MI 49006; Dillon G. Daudert, BS, Kalamazoo, MI 49006; James Jenkins, BS, Galesburg, MI 49053*

Learning Overview: The purpose of this presentation is to provide the forensic science community with a review of machine learning computational approaches, while assessing its utility to age-at-death estimation. After attending this presentation, attendees will better understand the essential nature of machine learning and the impediments to implementing such technology in applied contexts.

Impact on the Forensic Science Community: This presentation will impact the forensic science community by explicating the challenges of applying machine learning, a novel computational approach, to complex skeletal analysis, while providing guidance on best practices for future research.

This research examines the efficacy of a machine learning approach known as a Convolutional Neural Network (CNN) to the estimation of age-at-death by analysis of 3D scans of the pubic symphysis. Machine learning, a subfield of computer science, is a process that allows computers to execute decision-making tasks without specific human supervision. CNNs are especially successful in tasks relating to image categorization. CNNs have demonstrated competency greater than trained professionals in medical contexts.[1] A preliminary evaluation of a CNN's capacity to accurately assess age at death relative to trained osteologists was conducted to determine if this technology is potentially useful in forensic evaluation.

A CNN was built using the TensorFlow™ v1.7 open-source software library. To allow the CNN to learn associations between pubic symphysis morphology and age, it was provided a training batch of 3D images of the pubic symphysis from decedents of known age at death. Training images were created using the NextEngine® 3D Desktop Scanner. Scans were collected from individuals in the Hartnett-Fulginiti Collection of modern American pubic symphyses. The left aspect of the pubic symphysis of n=292 male individuals, aged 18–99 years, were scanned, processed, and provided to the CNN. After training, the CNN was tested on a novel selection of n=16 individuals chosen to proportionally represent the age distribution of the training sample. To provide a litmus for CNN performance, osteologists were recruited and asked to assess the same test sample. Volunteers, evaluating real bone, were asked to assign individuals to a Suchey-Brooks phase score.

Currently, results indicate that CNNs are not a viable approach to age-at-death estimation. CNN-generated ages are produced by a linear regression function output method which ubiquitously overestimates age in younger individuals, while underestimating the age of the elderly. Further, the CNN is prone to error where humans are not, such as misinterpreting postmortem damage that volunteers can easily recognize. The CNN does excel at assigning accurate age-at-death estimates for middle-aged individuals, which are accurate within ten years. However, because of the CNN's habit of producing middling values, these results must be regarded cautiously.

The trend toward middle-age value outputs is likely reflective of population biases in the training set, wherein middle-aged individuals account for more than half of all training data. Evidence that demonstrates CNN learning may be found in cases where both the CNN and observers anomalously misclassified individuals in accordance to non-normative morphology, such as marked overestimation of age in a 21-year-old displaying unusually advanced skeletal changes. This suggests that further training of the CNN with a deliberately biased data set to compensate for deficiencies in experience among the young and elderly will improve output results. However, meeting the training demands of a CNN, which often require many thousands of samples for high accuracy, may not be feasible given the nature of the data required. Further, natural morphological diversity may preclude refining age estimates much further beyond current methods. Such challenges, which are unique to anthropology, may preclude integrating machine learning approaches to applied osteology.

Reference(s):

1. Esteva, Andre, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature.* 542, no. 7639 (Feb 2017): 115–18.

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