Inception-V3 Architecture in Dermatoglyphics-Based Temperament Classification

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Introduction. Personality classification is one of the areas of behavioral psychology that focuses on categorizing individuals. Different factors constitute the main currents of human personality. These factors turned out to be complicated and sometimes yield a biased result (Green, 1997). Meanwhile, the entire human body reflects the character of its possessor more accurately than any set of questionnaires (Prabhu & Ravikumar, 2013). Dermatoglyphics is the scientific study of fingerprints (Prabha & Thenmozhi, 2014). Fingerprint patterns and ridge density are the viable bases in the classification of the personality of an individual. This uniqueness has expanded through research confirming parents' ability to identify their children's unique potentials through fingerprint analysis (Raizada et al., 2013). Bridging the gap between computer science and psychology is one of the biggest challenges of the study. Exploring the possibilities revolves around image processing, where fingerprints served as image input and a deep learning convolutional neural network model implemented in the Inception-v3 architecture is used to analyze and classify different fingerprint patterns finally associate with the classified prints to its corresponding temperament type.

Methods. The researcher employed a quantitative research design. The researcher used this particular design since it has something to do with formulating initial and specific hypotheses that guide the study. The researcher also utilized the experimental method that allowed the researcher to determine the accuracy of the inception v3 architecture in the fingerprint classification task and predicted the associated temperament personality type based on the fingerprint pattern classified through experimentation. On the other hand, the researcher utilized an iterative model design to develop the system that involved the simple implementation of a subset of the software specifications and iteratively improved the evolving versions until the full system is implemented (Wong, 2016). The fingerprint datasets used in the training, test, and validation phases are synthetic. These are generated using Anguli (Haritsa et al., 2018), a third-party tool employed by the researcher in producing the dataset. Synthetic fingerprints were used in the model creation because the fingerprints dataset is highly confidential and may reveal specific personal characteristics related to individuals' health status (Deliversky & Deliverska, 2018). The researcher utilized the inception-v3 architecture, an open-source architecture capable of retraining for a specific target task, in this case, fingerprint classification that will ultimately associate with the person's temperament. The temperament classification has four types, which are choleric, melancholic, phlegmatic, and sanguine. Each of the temperaments has its description. It is also possible that a person could have a combination of temperament. Aside from fingerprint pattern classification, the data was further manipulated to include noise and scratch with varying percentage levels to assess the accuracy of inception architecture. Noise is a pixel shift in an image (Kaur & Kaur, 2012), while scratch cuts in ridges (Arumuga et al., 2011). The noise and scratch percentage levels used for the training and testing phases are 0%, 25%, 50%, 75%, and 100%.

Results. In this study, the researcher used a total of 2, 250 synthetic fingerprint images to test the image recognition model that inception v3 built. The test result showed that inception-v3 was most effective in recognizing arch and whorl patterns, with each having a 99.78% accuracy rate. The left loop received the lowest accuracy rate at 79.56%, which was acceptably effective. The mean accuracy rate was 91.78, which revealed that Inception-v3 was generally useful in classifying fingerprint patterns, regardless of pattern classification.

Conclusion. The researcher concludes that the Inception-v3 Architecture created a model that produced an overall classification accuracy of 91.78%. The study also concludes that a successful transfer learning was done since originally, the architecture was pretrained for the ImageNet database, which does not include any fingerprint images. The researcher made the system training and model creation with the use of synthetic fingerprints. With the gathered results, it was very evident that the quality of images used during the user testing affected the classification accuracy results of the architecture by correctly categorizing the fingerprint pattern. There were basic data preparation procedures performed within the architecture. However, they were not enough to increase or even maintain the same accuracy percentage with system testing, where the researcher used synthetic fingerprints.

Practical Value of the Paper. Counseling is specifically concerned about providing advice and assistance to an individual in developing their educational plans, choice of appropriate courses, and choice of college (Reardon & Bertoch, 2018). The outcomes of the study would help the school guidance counselors to quickly assess and give appropriate advice to students without the hassle of conducting the standardized test and interpreting its results. Dhankar (2015) stated that dermatoglyphics could be exploited in career counseling to ensure that specific individuals follow the right career lines based on scientifically proven competencies.

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