

## Article

# Evaluating Impact of Race in Facial Recognition across Machine Learning and Deep Learning Algorithms

James Coe \* and Mustafa Atay \*

Department of Computer Science, Winston-Salem State University, Winston-Salem, NC 27110, USA

\* Correspondence: jcoe118@rams.wssu.edu (J.C.); ataymu@wssu.edu (M.A.)

**Abstract:** The research aims to evaluate the impact of race in facial recognition across two types of algorithms. We give a general insight into facial recognition and discuss four problems related to facial recognition. We review our system design, development, and architectures and give an in-depth evaluation plan for each type of algorithm, dataset, and a look into the software and its architecture. We thoroughly explain the results and findings of our experimentation and provide analysis for the machine learning algorithms and deep learning algorithms. Concluding the investigation, we compare the results of two kinds of algorithms and compare their accuracy, metrics, miss rates, and performances to observe which algorithms mitigate racial bias the most. We evaluate racial bias across five machine learning algorithms and three deep learning algorithms using racially imbalanced and balanced datasets. We evaluate and compare the accuracy and miss rates between all tested algorithms and report that SVC is the superior machine learning algorithm and VGG16 is the best deep learning algorithm based on our experimental study. Our findings conclude the algorithm that mitigates the bias the most is VGG16, and all our deep learning algorithms outperformed their machine learning counterparts.



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**Keywords:** facial recognition; machine learning; deep learning; dataset; bias; race; ethnicity; fairness; diversity

## 1. Introduction

Many biometrics exist to provide authentication for users while in a public setting [1], such as personal identification numbers, passwords, cards, keys, and tokens [2]. However, those methods can become compromised, lost, duplicated, stolen, or challenging to recall [2]. The acquisition of face data [3] is utilized for verification, authentication, identification, and recognition [4], and has been a decades-old computer vision problem [5]. The ability to accurately interpret a face allows for recognition to confirm an identity, associate a name with a face [5] or interpret human feeling and expression [6]. Facial recognition for humans is an easy task [5], but becomes a complex task for a computer [4] to perform like human perception [5]. Although image analysis in real-time [7,8] is feasible for machines, and significant progress has been achieved recently [9]. Automatic facial recognition remains a difficult task that is challenging, tough, and demanding [2]. Many attempts to improve accuracy in data visualization [3] still reach the same conclusion that artificial intelligence is not equal to human recognition when remembering a small sample size of faces [10], and numerous questions and problems remain [9].

A system needs to collect an image of a face to use as input to compare against a stored or previously recognized image for successful recognition. This step involves many variables that severely impact the capabilities for successful face recognition [4]. Many users want authentication in a public setting and most likely, using a mobile device leads to unconstructed environments [6] and non-controlled changes [11]. These changes lead to limitations on nonlinear variations [11], making data acquisition difficult [1]. This problem has persisted for over fifty years [6] and often contributes to differing results that cannot