# Certificate I: Understanding AI and Machine Learning in Africa

## Course AIML02: AI and Machine Learning in Africa

## Module 02: Application Case Studies

## Lecture 04: E-Commerce

Carnegie Mellon University
Africa

# Learning Objectives

1. Explain the concept of Know Your Customer (KYC)

2. Identify the problems for identity verification in Africa

3. Explain the technical details and performance of machine learning system for African face authentication

# Lecture Contents

# Know Your Customer

The "Know Your Customer" (KYC) process is a requirement that helps businesses identify their users and verify their credentials

(Keirstead et al. 2022)

# Know Your Customer

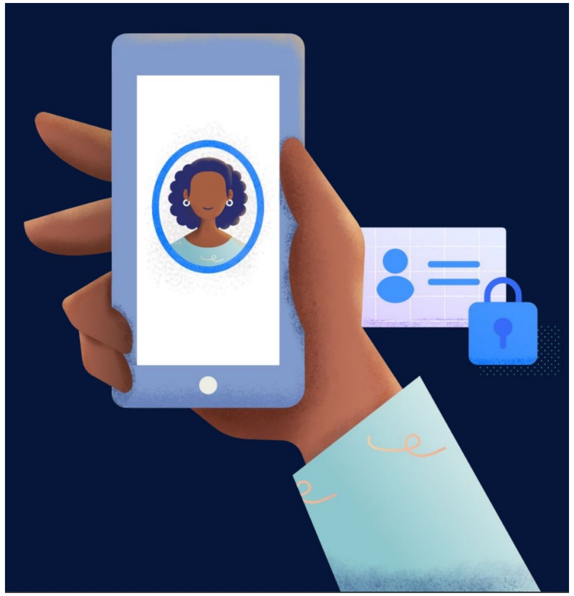
- 1 billion people do not have official proof of identity
- 1 in 2 women in low-income countries does not have an ID, limiting their access to critical services

IDENTIFICATION FOR DEVELOPMENT

https://id4d.worldbank.org/global-dataset

# Know Your Customer

- The solution is digital identity
- The ability to prove you are who you say you are online



https://smileidentity.com/img/state-of-kyc-report_2022h1.pdf

# Know Your Customer

Two reasons for conducting KYC checks

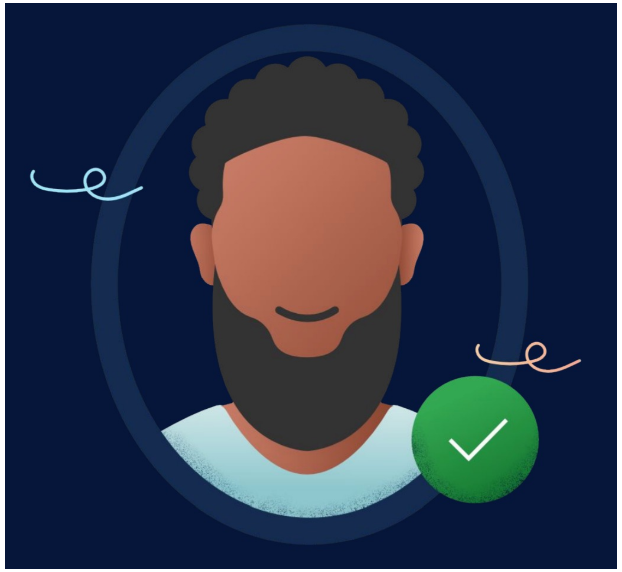
1. Regulatory compliance
2. Fraud prevention

Conventional approaches are time-consuming and expensive

https://smileidentity.com/img/state-of-kyc-report_2022h1.pdf

# Know Your Customer

Biometric KYC can assist by confirming that the person providing a credential (an ID number) is who they say they are



https://smileidentity.com/img/state-of-kyc-report_2022h1.pdf

# Know Your Customer

Biometric KYC can assist by confirming that the person providing a credential (an ID number) is who they say they are

Biometric systems that use deduplication can also be used to ensure a person is only who they say they are, i.e., that they haven't created duplicate identities

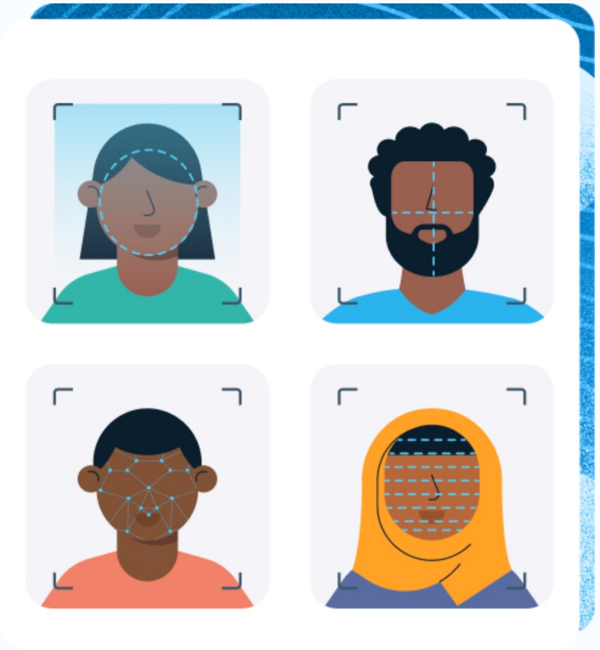
https://smileidentity.com/img/state-of-kyc-report_2022h1.pdf

# Smile Identity

## AI Optimized for Africa

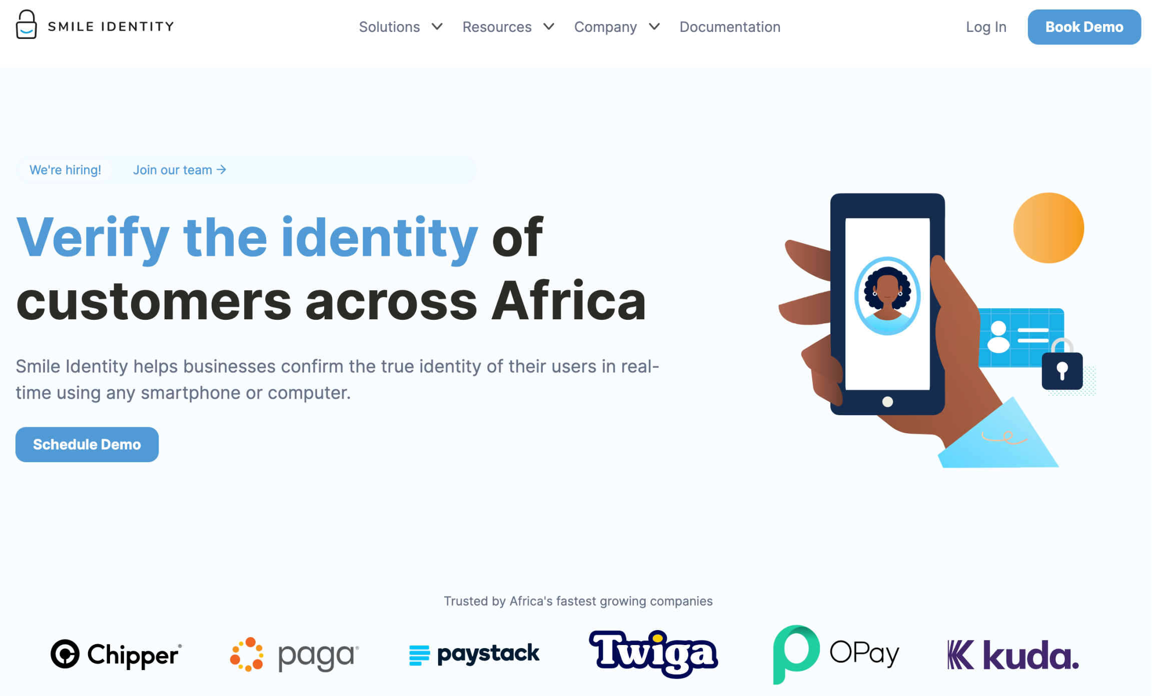
Our SmartSelfie technology has been trained on over 5 million African faces. With a 99.8% accuracy rate, you can be sure you know who your customers are.

- Match faces to documents and official ID photos
- Perform sophisticated liveness and anti-spoof checks
- Facial detection that is highly accurate for African faces



www.smileidentity.com

# Smile Identity




www.smileidentity.com

# Data Centric Face Recognition for African Face Authentication

## SmileID

- Commercial system
- Frontal-face identity verification
- Mobile handsets
- Targeting African users
- Banking, lending, ride-sharing, …

**Data Centric Face Recognition for African Face Authentication**

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**Abstract**

*We present the SmileID face recognition system, a commercial system for frontal-face identity verification on mobile handsets in Africa. Our work is a case study in building and deploying a real-world face recognition system that must work primarily on non-caucasian faces. Unlike commercial systems that aim to reduce bias by minimizing accuracy disparity between light-skinned and dark-skinned faces in many lighting conditions and poses, our system focuses specifically on frontal face smartphone-based authentication of dark-skinned, African faces. While much research work has focused on improving model structures and loss functions to reduce modal bias, we show that a data-centric approach – training a state of the art network on African faces – yields strong results. We observe gaps between the accuracy numbers on dark-skinned faces reported by commercial "multi-purpose" systems like AWS Rekognition and their real-world performance once we add the constraints that the images come from low-power handsets as selfies in frontal-only poses. Our model outperforms Rekognition on a benchmark dataset for frontal authentication and achieves an 11% gain over a baseline ArcFace implementation in this setting by training on an African dataset. On the other hand, it also improves homogeneity by 16% and completeness by 21%.*

split out by ethnicity, gender, and skin tone [2] [4] [10] [17] [9]. What's more, much research effort has gone into optimizing these models to perform well across a variety of lighting conditions and poses that match the applications of interest of a majority-western customer base. Recently, commercial face recognition providers such as AWS Rekognition, Microsoft, and Google have come under significant criticism for releasing biased models and for enabling surveillance applications. Their response has been to acquire more balanced training data and assess their models for bias, often defined as the accuracy disparity between subgroups of the data, such as dark-skinned women and light-skinned men [13]. However, their goal has remained building robust general-purpose face recognition.

We present a face recognition system targeted specifically at non-surveilance, frontal face authentication to empower smartphone-based authentication in Africa for use cases like banking, lending, or ride sharing. Existing datasets do a poor job of assessing face recognition systems for this use case and that most of existing facial recognition commercial systems, including AWS Rekognition, perform below recently published benchmarks on dark-skinned faces [23] [1].

Our model is a facial embedding model based on the ArcFace loss function [3] that is transfer-learned using a proprietary dataset of African faces. Like most

(Uwizera et al., 2020)

# Data Centric Face Recognition for African Face Authentication

## Motivation

AIML01, Module 2, Lecture 2: Connectionist Approaches to AI, and
AIML02, Module 3, Lecture 1: Healthcare

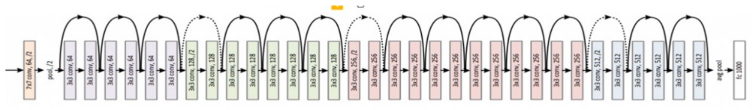
- Deep Convolutional Neural Networks (CNNs) provide human-level performance on many datasets
- Mainly been trained and tested with data featuring predominantly Caucasian faces
- Optimized to perform well in lighting conditions and poses that match the applications of interest to Western customers
- The goal of commercial face recognition providers is robust general-purpose face recognition
- Need Africa-targeted model that works well on mobile handsets

# Data Centric Face Recognition for African Face Authentication

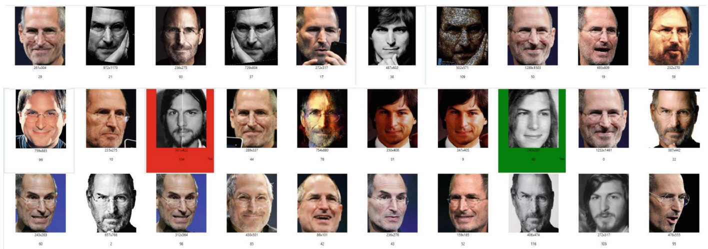
## Overview of the SmileID system

AIML01, Module 2, Lecture 2: Connectionist Approaches to AI, and AIML02, Module 3, Lecture 1: Healthcare

- ResNet15 CNN
  (He et al., 2016)



- Pre-trained on MS-Celeb1M dataset
  (Guo et al., 2016)



- Transfer learning with a proprietary dataset

AIML01, Module 3, Lecture 1: AI Applications in Medicine and AIML02, Module 3, Lecture 1: Healthcare

- Tested with three data sets, compared to two baseline models

# Data Centric Face Recognition for African Face Authentication

## Details of the SmileID system

- ResNet15 CNN
  (He et al., 2016)
- Pre-trained on MS-Celeb1M dataset
  (Guo et al., 2016)
- Transfer learning with a proprietary dataset
- Tested with three data sets, compared to two baseline models

Improve accuracy of identity verification by maximizing intra-class compactness and interclass separability

Achieved by learning an effective embedding model

Uses the ArcFace loss function (Deng et al., 2019)

- Quantifies how well predicted class labels agree with ground-truth labels
- Low loss implies high level of agreement (& vice versa)
- Goal of training is to minimize the loss function and, hence, increase classification accuracy

# Data Centric Face Recognition for African Face Authentication

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A popular large open dataset for face recognition consisting of predominantly white faces

During training and verification, image values are normalized between zero and one, a face is located, cropped and aligned to a 112x112 bounding box

# Data Centric Face Recognition for African Face Authentication

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This is the FDD dataset in the target article

Images were collected from individuals using third-party apps built by Smile Identity's customers in Africa.

22,330 images:
70% for training
30% for testing

Only the last 4 ResNet layers are adjusted:
(the model learn the elements of the non-Caucasian recognition task without losing the low-level features learned during the pre-training phase)

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Blend of 500 images from the Celeb-1M dataset

Blend of 500 images from the Smile Identity FDD dataset

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Data augmentation is used in both phases to increase robustness:

- Random saturation and brightness is applied to training images with 50% probability
- Vertical flipping introduced with 40% probability
- Noise is added with 10% probability

- Tested with three data sets, compared to two baseline models

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Dataset 1: LFW dataset
Labelled Faces in the Wild (Huang et al. 2008)

Dataset 2: FDD proprietary dataset
(30% of the 22,330 images)

Dataset 3: LFWB dataset
(Random pairs of matching dark faces from LFW dataset)

Baseline 1: AWS Rekognition

Baseline 2: ArcFace without transfer learning

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Evaluation portion of the proprietary Smile Identity dataset

Baseline Models

Transfer learning model

| Model | LFW | FDD | LFWB |
|---|---|---|---|
| AWS Rekognition | 99.2 | 97.4 | 96 |
| Arcface Baseline | **99.3** | 88 | 98.1 |
| Optmized Arcface | 98.8 | **98.9** | **99.8** |

11% gain over the baseline ArcFace model when tested on African faces

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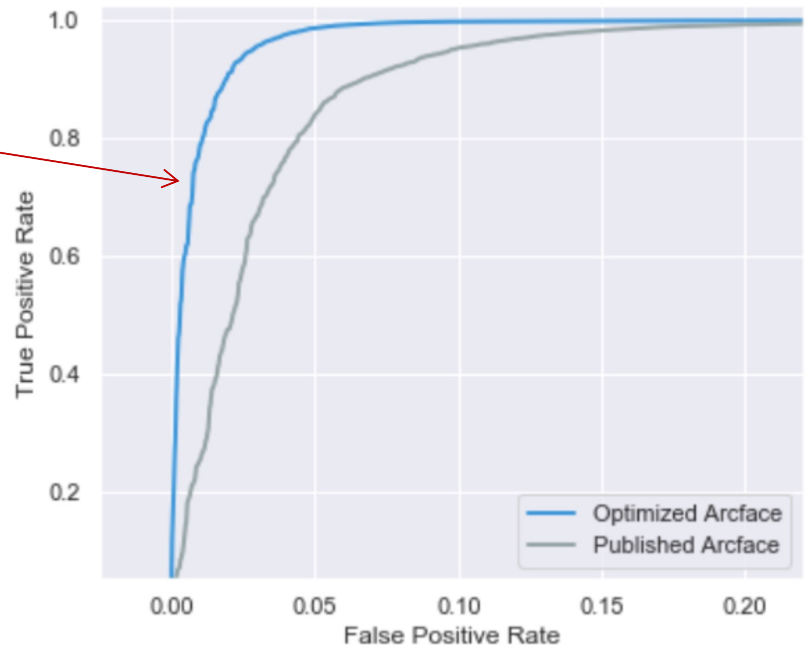
ROC (receiver operating characteristic) curve for the optimized ArcFace model after transfer learning

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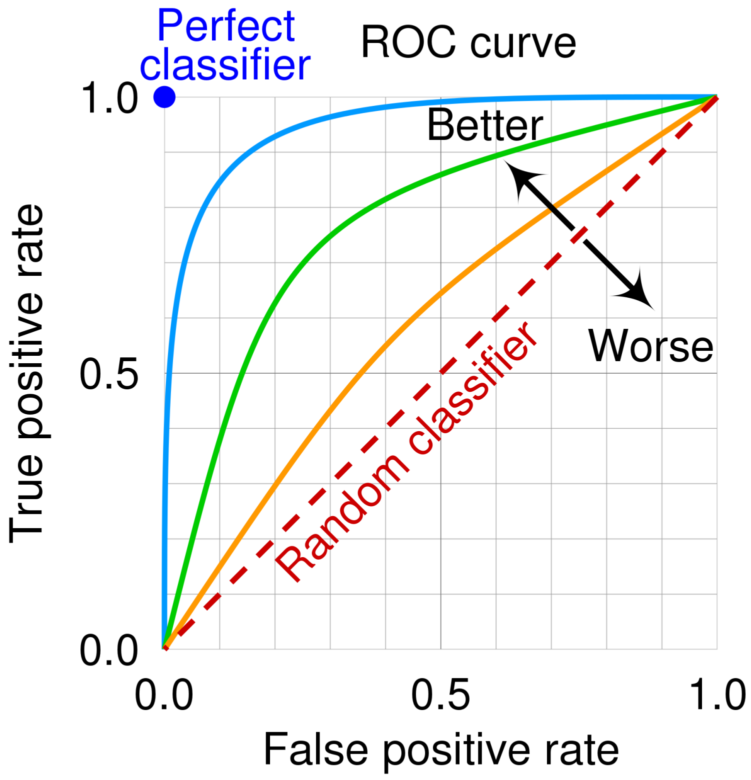


https://en.wikipedia.org/wiki/Receiver_operating_characteristic

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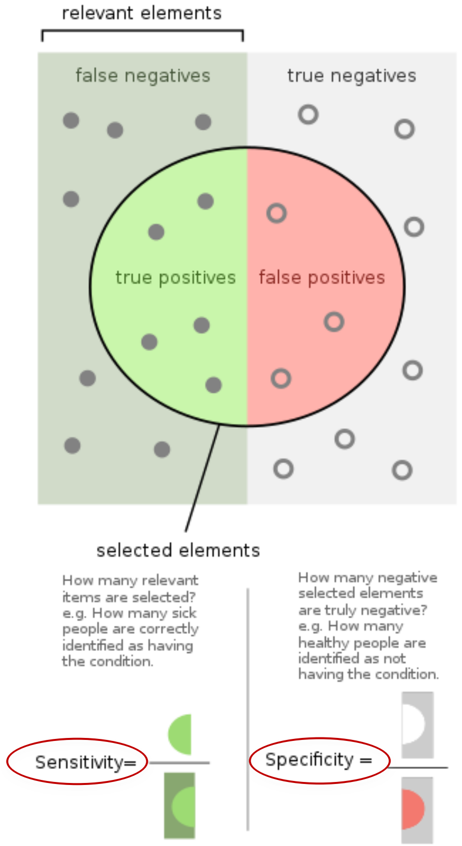


https://en.wikipedia.org/wiki/Sensitivity_and_specificity

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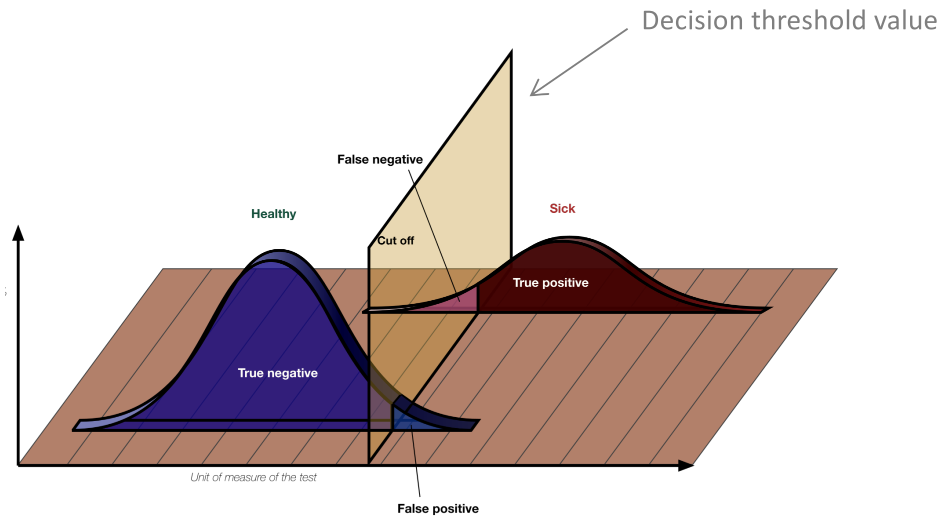


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- Transfer learning with a proprietary dataset

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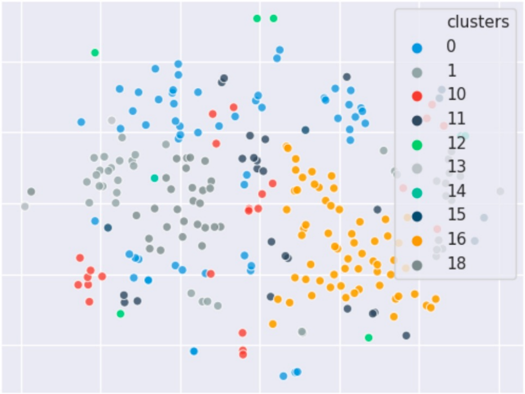
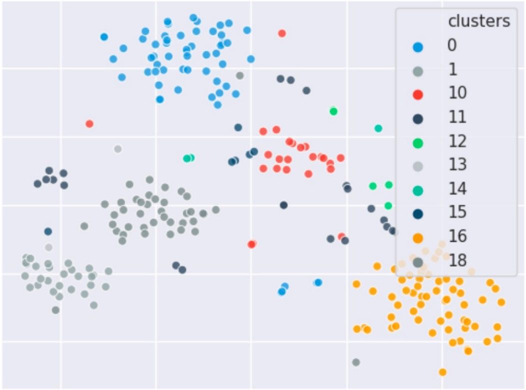



Baseline ArcFace embedding clusters for African faces




Optimized transfer learning ArcFace embedding clusters for African faces

# Lecture Summary

1. The know your customer process is essential for avoiding fraud, both in financial transactions and when onboarding customers and clients
2. Digital identity verification is key step in this, but most systems do not perform well in the African context
3. Smile Identity have developed an effective face recognition technique that outperform other approaches
4. It uses a pretrained ResNet50 deep convolutional network and transfer learning using a proprietary Smile Identity training set

# Recommended Reading

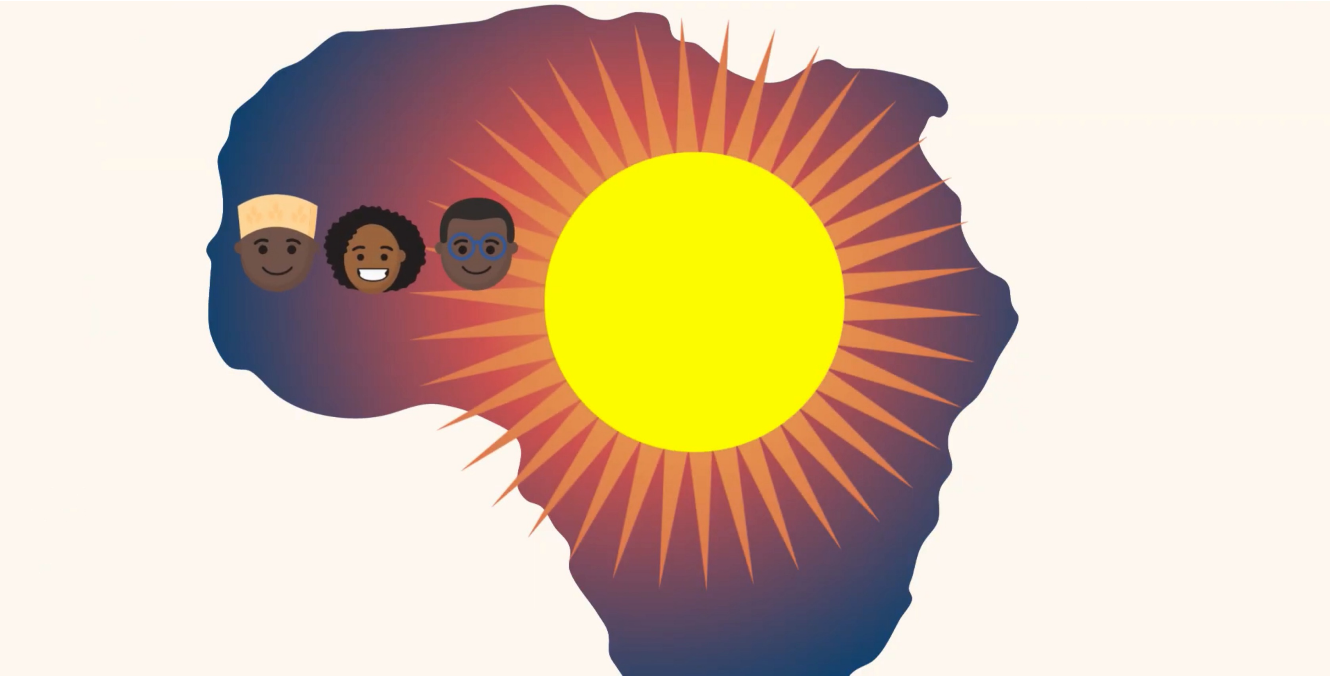
Uwizera, D., Bares, W., Voss, C. (2020). Data Centric Face Recognition for African Face Authentication, Smile Identity.
https://cdn.smileidentity.com/Smile_Identity_Model_Paper-CVML.pdf

# Recommended Reading

Keirstead, M, Straub, M., Orina, L, Wambua, R., Scheybani, N., and Williams, G. (2022). State of KYC in Africa, H1 2022 Report.
https://smileidentity.com/img/state-of-kyc-report_2022h1.pdf

# Recommended Video

Smile Identity Video
https://www.youtube.com/watch?v=g1vHLH4gWyo



# References

D4D Data: Global Identification Challenge by the Numbers, World Bank.
hthttps://id4d.worldbank.org/global-dataset

Deng, J., Guo, J., Xue, N., and Zafeiriou, S. (2019). Arcface: Additive angular margin loss for deep face recognition, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4690–4699.
https://openaccess.thecvf.com/content_CVPR_2019/papers/Deng_ArcFace_Additive_Angular_Margin_Loss_for_Deep_Face_Recognition_CVPR_2019_paper.pdf

Guo, Y., Zhang, L., Hu, Y., He, X., Gao, J. (2016). MS-Celeb-1M: A Dataset and Benchmark for Large-Scale Face Recognition. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (eds) Computer Vision – ECCV 2016. ECCV 2016. Lecture Notes in Computer Science, vol 9907. Springer.
https://doi.org/10.1007/978-3-319-46487-9_6

He, K., Zhang, X., Ren, S., and Sun, J. (2016). "Deep residual learning for image recognition." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770-778.
https://arxiv.org/pdf/1512.03385.pdf

# References

Huang, G. B., Ramesh, M., Berg, T., and Learned-Miller, E. (2008). Labeled faces in the wild: A database for studying face recognition in unconstrained environments, in: Workshop on Faces in "Real-Life" Images: Detection, Alignment, and recognition. Marseille, France.

http://vis-www.cs.umass.edu/lfw/lfw.pdf